Three Essays on Risk Sharing

D I S S E R T A T I O N

zur Erlangung des akademischen Grades

doctor rerum politicarum

(Doktor der Wirtschaftswissenschaft)

eingereicht an der

Wirtschaftswissenschaftlichen Fakultät

der Humboldt-Universität zu Berlin

von

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Tag des Kolloquiums: 30.10.2020

Abstract

This thesis contains three chapters that empirically study the impact of risk on firm level decisions and firms' ability to share risks with their stakeholders. The firms that are studied in all three papers are hotels in Austrian ski resorts.

The first chapter provides a comprehensive study of the risk sharing between Austrian ski hotels and their stakeholders. We obtain two main results. The first main finding is that the entrepreneurs share snow-induced sales risk with their workers, while the dividend payments to the entrepreneurs are not affected by these exogenous shocks to firms' sales. This finding opposes the view of the entrepreneur as a risk taker. We find that hotels insure their workers against weather-induced sales shocks only if the shocks are highly temporary during the winter-season.

The second main result is that entrepreneurs share exogenous sales risk with their house-banks. The second chapter empirically analyzes interbank lending using a sample of banks in Austrian ski resorts. The banks are subject to liquidity shocks due to weather-induced demand shocks in ski tourism. We analyze the effect of these shocks on interbank lending and borrowing. In our analysis, we use snow in ski resorts as an instrumental variable for the possibly endogenous demand shocks. The analysis reveals that banks reduce their net lending to other banks at times when they need to provide liquidity to their non-bank customers.

The third chapter empirically studies how small-firm employment respond to labor productivity risk. We show that this depends on the equity capital of local banks. We find that an increase in the risk of transitory productivity shocks reduces firms' willingness to commit to employing workers. This effect is stronger if local banks have less equity capital. It appears that a lack of bank equity reduces firms' capacity to take labor productivity risk.

Zusammenfassung

Diese kumulative Dissertation untersucht in drei Kapiteln den Effekt von Risiko auf Firmenentscheidungen und die Fähigkeit von Firmen, Risiken mit ihren Stakeholdern zu teilen. Die betrachteten Firmen sind Skihotels in österreichischen Skigebieten.

Das erste Kapitel ist eine umfassende Studie zur Risikoteilung zwischen Skihotels und ihren Stakeholdern. Es gibt zwei hauptsächliche Ergebnisse. Erstens wird gezeigt, dass Unternehmer Wetterrisiko mit ihren Arbeitnehmern teilen, selbst aber kein Wetterrisiko tragen. Dieses Ergebnis ist in Widerspruch zur Vorstellung des Unternehmers als Risikoträger. Das zweite Ergebnis ist, dass Firmen Wetterrisiko mit ihrer Hausbank teilen.

Das zweite Kapitel untersucht anhand von Banken in "osterreichischen Skigebieten die Rolle des Interbankenmarkt. Die Banken in Skigebieten sind Liquiditätsschocks ausgesetzt, die durch touristisch bedingte Nachfrageschocks erzeugt werden. Der Effekt dieser Schocks auf die Kredittätigkeit der Banken ist Gegenstand dieser Studie. Das Ergebnis der Studie ist, dass Banken mehr Kapital auf dem Interbankenmarkt beschaffen, wenn sie ihren Kunden in der Realwirtschaft in Folge eines Nachfrageschocks Liquidität gewähren müssen.

Das dritte Kapitel untersucht, wie die Beschäftigungspolitik von kleinen Firmen auf Risiko in der Arbeitsproduktivität reagiert. Ein Ergebnis ist, dass das abhängig ist von der Kapitalisierung des lokalen Bankenmarktes. Es wird gezeigt, dass eine Zunahme in transitiven Arbeitsproduktivitätsrisiko die Bereitschaft der Firmen verringert Arbeitnehmer einzustellen. Dieser Effekt ist umso stärker, je schlechter lokale Banken kapitalisiert sind. Es scheint, als würde ein Mangel an Kapital in Bankensektor die F"ahigkeit von Skihotels mindern, Arbeitsproduktivität einzugehen.

Contents

An introductory summary

This thesis contains three papers that empirically study the impact of risk on firm level decisions and firms' ability to share risks with their stakeholders. The firms that are studied in all three papers are hotels in Austrian ski resorts. As Austrian ski hotels principally are small firms, this thesis adds to the literature on the risk management of small firms. Small firms are an important part of the economy as they employ a large fraction of the workforce in the economy (see U.S. Census Bureau (2015)). In addition, small firms are known to be bad in managing economic shocks (see Farrell and Wheat (2019)).

The hotels cater to tourists whose demand depends on the snow conditions in the resorts. Hence, snow represents a source of sales and, therefore, liquidity for the hotels. However, snow is uncertain and snow risk causes liquidity risk for the ski hotels. Snow is an exogeneous variable, which is plausibly not influenced by any firm level variable. Hence, the results in all three papers can be interpreted as causal effects of risk.

By focusing on snow-induced risk, all three papers in this thesis add to the literature on the economic adaptation to climate change. One observation of climate change is that weather risk is increasing over time. The results in this thesis help to understand the economic consequences of the increase in weather risk. Ski hotels react to increasing risk by not hiring or firing employees. We also highlight one channel that modulates this effect: Liquidity provision by banks. If the banks close to the hotels are poorly capitalized, hotels' display even less willingness to hire workers. Thus, the evidence found in this thesis suggests that one outcome of climate change is rising unemployment in industries that depend on weather.

The first paper, "Who bears entrepreneurial risk?", provides a comprehensive study of the risk sharing between Austrian ski hotels and their stakeholders.

The stakeholders that are analyzed are the hotels' workers, their house-banks, their suppliers of material inputs and services, and their landlords. Theoretically, workers should be insured by firms against idiosyncratic shocks (see Knight (1921), Azariadis (1975)). In addition, under certain conditions, firms' house-banks (see Boot (2000)) and their suppliers (see Petersen and Rajan (1997)) should be willing to provide liquidity to a firm when it is hit by a shock. We use the data on Austrian ski hotels to empirically analyze who bears the snow-induced sales risk. We obtain two main results. The first main finding is that the entrepreneurs share snow-induced sales risk with their workers, while the dividend payments to the entrepreneurs are not affected by these exogenous shocks to firms' sales. This finding opposes the view of the entrepreneur as a risk taker suggested by Knight (1921). The risk-sharing with the workers happens at the extensive margin, i.e. firms hire or fire workers given the sales shocks. We find that hotels insure their workers against weather-induced sales shocks only if the shocks are highly temporary *during* the winter-season. The second main result is that entrepreneurs share exogenous sales risk with their house-banks. The interest payments of the hotels are lower after the hotel experienced a bad winter. The risk sharing between the hotels and their house-banks is prevalent only in areas that display high bank-level competition - a result that is in line with the theory of Boot and Thakor (2000). We do not find evidence for risk sharing between the hotels and their other stakeholders, i.e. their suppliers or landlords.

The second paper, "Interbank Lending and Banks' Supply of Liquidity Insurance to the Real Sector" co-authored with Alex Stomper, empirically analyzes interbank lending using a sample of banks in Austrian ski resorts. The banks are subject to liquidity shocks due to weather-induced demand shocks in ski tourism. We analyze the effect of these shocks on interbank lending and borrowing. In our analysis, we use snow in ski resorts as an instrumental variable for the possibly endogenous demand shocks. The analysis reveals that banks reduce their net lending to other banks at times when they need to provide liquidity to their non-bank customers. Our evidence adds to the literature regarding the role of the interbank market in banks' liquidity creation. It highlights effects of a specific type of liquidity creation, i.e., the liquidity insurance banks provide to the real sector (see Holmstrom and Tirole (1998)). We find that shocks triggering this insurance reduce banks' longer-term lending to other banks, but we find no effects on short-term net lending. Moreover, we observe particularly strong effects for (i) banks with regionally focused operations, (ii) banks with higher equity ratios, (iii) banks that face relatively low levels of snow risk, and (iv) banks with a geographically diversified branch network.

The third paper, "Risk and Employment: Banking on Snow" co-authored with Thomas Schober, Alex Stomper, and Rudolf Winter-Ebmer, empirically studies how small-firm employment respond to labor productivity risk. We show that this depends on the equity capital of local banks. The analysis in this paper tests the foundations of models from the macro-finance literature (see Arellano, Bai, and Kehoe (2019) and Quadrini (2017)). In these models firm-level employment decreases if the volatility of labor productivity increases. Our analysis is based on a truly quasi-experimental setting. We use highly granular data about a sample of small firms employing workers whose productivity depends on the weather. The data allow us to cleanly identify the causal effect of labor productivity risk on the firms' employment. We find that an increase in the risk of transitory productivity shocks reduces firms' willingness to commit to employing workers. This effect is stronger if local banks have less equity capital. It appears that a lack of bank equity reduces firms' capacity to take labor productivity risk. Our evidence also highlights that bank capitalization matters for economic adaptation to climate change by reducing the effects of increased weather variability on small-firm employment.

References

Arellano, C., Y. Bai, and P. J. Kehoe (2019). Financial frictions and fluctuations in volatility. *Journal of Political Economy 127*(5), 2049–2103.

Azariadis, C. (1975). Implicit contracts and underemployment equilibria. *Journal of Political Economy 83*(6), 1183–1202.

Boot, A. (2000). Relationship banking: What do we know? *Journal of Financial Intermediation 9*(1), 7–25.

Boot, A. and A. Thakor (2000, 04). Can relationship banking survive competition? *The Journal of Finance 55*.

Farrell, D. and C. Wheat (2019). The Small Business Sector in Urban America. https://institute.jpmorganchase.com/content/dam/jpmc/jpmorgan-chase-and-co/institute/pdf/institute-small-business-sector-report.pdf, (Accessed: 2020-05-17).

Holmstrom, B. and J. Tirole (1998). Private and public supply of liquidity. *Journal of Political Economy 106*(1), 1–40.

Knight, F. H. (1921). Risk, uncertainty and profit, 1921. *Library of Economics and Liberty*.

Petersen, M. and R. Rajan (1997). Trade credit: Theories and evidence. *Review of Financial Studies 10*(3), 661–91.

Quadrini, V. (2017). Bank liabilities channel. *Journal of Monetary Economics 89*, 25–44.

U.S. Census Bureau (2015). Statistics of U.S. Businesses. https://www.census.gov/programs-surveys/susb/data/tables.2015.html, (Accessed: 2020-05-17).

Who bears entrepreneurial risk?

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Abstract

This paper analyzes whether entrepreneurs share sales risk with their firms' stakeholders. We study a sample of small, family-owned firms exposed to snow risk as a source of exogenous sales risk: Austrian ski hotels. Our main finding is that the entrepreneurs share exogenous sales risk with their workers, while the dividend payments to the entrepreneurs are not affected by exogenous shocks to firms' sales. This finding opposes the view of the entrepreneur as a risk taker suggested by Knight (1921). In addition, we find that entrepreneurs share exogenous sales risk with their house-banks and that this is prevalent only in areas that display high bank-level competition. Snow risk is a weather risk and linked to Climate Change. It follows that the findings in this paper are relevant for policy makers to understand the consequences of climate change on unemployment and the health of local banking markets.

1 Introduction

Knight (1921) describes the entrepreneur to be the "confident and venturesome", who assumes risk and insures her "doubtful and timid" workforce by guaranteeing them a stable income and employment. This statement, later formalized by Kihlstrom and Laffont (1979), suggests that entrepreneurs may have lower degrees of risk aversion than the remaining population. In a Forbes article, Brown (2013) states a different view on entrepreneurs' taste for risk. He claims that entrepreneurs "don't like risk. They accept it as part of the game and then work extremely hard to reduce it to a minimum." His view suggests that entrepreneurship is not caused by the taste for risk but the ability to manage the exposure towards the risk. It is not necessary that entrepreneurs and workers have a different degree of risk aversion. The seemingly less risk averse behavior of entrepreneurs may be explained by superior access to capital markets. This allows them to better diversify risk than their workers. Therefore, the entrepreneurs would behave as if they were less risk averse than their workers.

However, ownership in small, privately held firms is highly concentrated. From a modern portfolio theory standpoint, entrepreneurs' portfolios are often not sufficiently diversified, and entrepreneurs are overly exposed to their firms' idiosyncratic risk (see Moskowitz and Vissing-Jorgensen (2002)). As a result of their portfolio not being well-diversified, entrepreneurs of small, privately held firms might have a great distaste for their firms' risk and thus might try to share it with other parties.

This leads to the main question addressed in this study: Do entrepreneurs bear their companies' risk themselves or can they share it with their stakeholders? For example, in the model of Herranz, Krasa, and Villamil (2015), entrepreneurs can manage their personal exposure to their firms' risk by the use of outside capital in the form of bank debt.[1] We use risk created by unexpected annual fluctuations of firms' sales revenues, and analyze if entrepreneurs' dividend payouts in a given year are sensitive to their firms' sales revenue in this year. In addition, we test whether entrepreneurs are able to share risk with their workers (as opposed to Knight's view of the entrepreneur), with their house-banks, or with other stakeholders of their firms, i.e. their suppliers and their landlords, by adjusting the contemporaneous payments to them after realizing a sales shock.

We approach the research question by analyzing data on Austrian ski hotels. The sample choice is motivated by a number of properties of the Austrian ski hotel industry. Usually, Austrian ski hotels are managed by their owners, i.e. the entrepreneurs.[2] For their owners, the proceeds from the hotel typically constitute the primary source of income. In this industry, firms do not issue public debt or equity, hence bank debt is their only source of outside capital available.

Austrian ski hotels employ a high number of seasonal employees. In a related study, Baumgartner, Schober, Stomper, and Winter-Ebmer (2020) show that for the average firm in the Austrian tourism industry, the share of seasonal employees is about 50% in the peak season. In addition, Austrian ski hotels are small, i.e. the largest firm in our sample employs less than 200 employees. Small firms are an important part of the economy, nevertheless their coverage in research is lower than that for large, publicly traded firms.[3] At the same time, small firms seem to be especially exposed to sales shocks. According to Farrell and Wheat (2019), half of the small firms in U.S. would not survive more than two weeks without sales revenues.

[1] In the case of a negative shock, the entrepreneur is able to default if optimal for her.

[2] According to a study by Doerflinger, Doerflinger, Gavac, and Vogl (2013), 93% of the firms in the industry are family owned

[3] In the U.S., small firms employed 47.5% of the workforce in 2015 (see U.S. Census Bureau (2015)), and produced 45% of GDP in 2010. (see U.S. Small Business Administration (2018)).

Finally, Austrian ski hotels are subject to an exogenous source of risk to their demand: Weather risk. The demand for ski hotels' services depends on snow in a non-linear way. If there is too little snow to do skiing, customers who haven't booked will not book nights accommodation and customers who have already booked will consider canceling their existing bookings.

The number of snow cannons in entire Europe in 2007, one year after the end of our sample period, accounted for only 15% of the number of snow cannons in Austria alone only eight years later (see Salzburger Nachrichten (2015)).[4] Hence, snow influences hotels' sales revenues through the demand by ski tourists.

We measure the industry wide exposure of ski hotels' sales to sales risk using a similar strategy as Stulz and Williamsom (1996). We find that one additional day of snow increases the sales of the hotels by about 1,700 Euros, which equals 0.67% of the within standard deviation of hotels' sales. Moreover, the effect is mainly triggered by losses in sales during bad winters. The exposure of Austrian ski hotels to exogenous snow risk allows us to use snow days as an instrumental variable for firm level sales and identify causal effects.

We find that weather induced sales shocks have no statistically significant effect on contemporaneous payouts to entrepreneurs, i.e. that the dividends are not systematically lowered after an exogenous decrease in sales. In addition, we find that hotels' workers are not sheltered from weather induced sales risk. For a one Euro decrease in sales, we observe a 21 cent decrease in the total wage bill of the hotel. This result is driven by the extensive margin, i.e. hotels react to negative weather induced sales shocks by firing employees. The finding that entrepreneurs are not exposed to contemporaneous sales risk themselves

[4] To the best of our knowledge, Austrian ski hotels did not hedge snow risk by the use of derivatives or insurance. Payoffs from weather insurance or derivatives could offset the snow induced risk borne by the entrepreneur.

but share it with their employees is surprising, as it opposes the view of the entrepreneur as a risk-taker by Knight (1921).

Our results on risk sharing between hotels and their house-banks suggest that hotels are able to share sales risk with their banks by adjusting loan related payments. The payments to banks are lower after the hotels have realized a negative sales shock. We do not find that this is caused by the banks forgiving part of the debt. Instead, we find that hotels seem to be able to adjust or defer their interest payments. This result is consistent with the results in Giroud, Mueller, Stomper, and Westerkamp (2011).[5] We find that hotels are able to share both temporary and persistent sales risk with their banks.

We do not find evidence for risk sharing between hotels and their suppliers. This is not so surprising as we observe risk sharing between hotels and their banks, and the previous literature on trade credit suggests that suppliers might take the role of banks whenever the banking sector is underdeveloped (see Petersen and Rajan (1997)). We do also not find evidence for risk sharing between hotels and their landlords. This might be due to the reason that the majority of the hotels in our sample own most of their buildings and rent is therefore only a small fraction of sales that can be paid easily by the hotels.

We test whether hotels' risk sharing with their workers and their house banks depends on the persistence of the sales shock. By nature, snow induced sales shocks are not persistent from one winter season to another. However, we can distinguish between persistent and temporary sales shocks *within* the winter season. During the starting weeks of the winter season, negative snow shocks are temporary because additional snow is likely to fall in the following weeks. In the ending weeks of the winter season, negative snow shocks become permanent, as additional snow fall is less probable in the near future.

[5] They claim that for hotels which experienced negative demand shocks, debt forgiveness would constitute a windfall gain.

We find that firms do insure workers against shocks which are temporary *within* the winter season. In contrast, in the end of the season, when negative snow shocks become persistent for that winter season, workers are not insured. These two findings are in line with the previous literature (see Guiso, Pistaferri, and Schivardi (2005), Guertzgen (2014), Ellul, Pagano, and Schivardi (2018)). We do not find a difference in risk sharing between hotels and their house banks for temporary and persistent *within-season* sales shocks. Hotels are able to share both kinds of shocks with their house-banks. This is not surprising, as the duration of the lending relationship is very likely to exceed one winter season and, therefore, persistent *within-season* sales shocks are still considered temporary by the hotels' house-banks. The same statement does not necessarily hold for the hotels' workforce, given ski hotels employ a high fraction of seasonal workers.

We perform sample splits to test whether hotels' risk sharing with their workers and their house banks is especially pronounced for hotels with certain characteristics. We find risk sharing between firms and their workers at both small and large firms. Only firms which are not highly indebted are able to share sales risk with their workforce. We have the following interpretation of this finding: It is hard for hotels in financial distress to attract seasonal employees.[6] As a result, the hotels in financial distress employ mainly key employees (probably family members). These employees are not laid off in times of an adverse shock and they do not extract money from the hotel in times of a positive sales shock.

Risk sharing between hotels and workers primarily takes place in counties with high levels of labor market tightness. In these counties, it is relatively easy for workers to find a new job, hence the provision of employment insurance in return for a lower wage is not as valuable for these workers as it is for

[6] We find those hotels to significantly smaller than the remaining hotels.

workers in counties which exhibit low labor market tightness. Risk sharing between hotels and banks does not differ significantly between small and large hotels. Banks share risk only with hotels which are not in the highest 25% of the distribution of financial leverage, i.e. not too close to financial distress. We find that only banks in local banking markets that experience high levels of bank competition engage in risk-sharing with their borrowers. This result supports the model of Boot and Thakor (2000) rather than that of Petersen and Rajan (1995). Boot and Thakor (2000) suggest that relationship lending activity is higher in competitive banking environments.

We chose to study snow risk not only because it is exogenous but also because it is increasingly relevant topic. Snow risk is a weather related risk and it is supposed to increase in the future due to climate change. Other industries, like agriculture or construction, are also exposed to weather risk. These industries share some similarities with the Austrian ski hotel industry. They employ a large number of seasonal employees and the group of small firms has a significant market share. The results of this study are therefore relevant understanding and predicting the economic consequences of climate change in exposed industries.

The paper is organized as follows. Section 2 provides insights about the Austrian hotel industry. Section 3 presents the empirical methodology and the hypotheses we test. Section 4 describes the data. Sections 5 presents the results. Section 6 concludes.

1.1 Related literature

To the best of our knowledge, this is the first paper that analyzes risk sharing by firms with their workers *and* their creditors *and* their suppliers in one comprehensive study.

The paper is related to multiple strands of the literature. First, it is related to the literature on risk sharing between firms and their employees. The idea that entrepreneurs insure their workers against risk dates back to Knight (1921). Kihlstrom and Laffont (1979) provide a general equilibrium model, in which risk aversion determines the decision whether individuals become entrepreneurs or workers. Azariadis (1975) proposes a model where risk-neutral entrepreneurs, in exchange for a lower average wage, provide insurance to risk-averse workers by sheltering their wages and their employment from firm level shocks.

The paper which is most closely related to this analysis is the paper by Rettl, Stomper, and Zechner (2019). Rettl et al. (2019) analyze how industry-wide and hence systematic risk is shared between firms' shareholders and their workers in the electricity industry. Their findings are different from the results in this paper, i.e. that workers' wage bills are isolated from risk, whereas dividend payments to shareholders are not. The authors provide the following explanation for their results: The firms that are analyzed take the beta of their owners as given, i.e. the shareholders are not negatively affected by increases in systematic risk by the firm. This argument, however, does only make sense for large, publicly held firms. For the firms in our sample which are small and owner-managed, we would expect different results. According to a survey by Brav, Graham, Harvey, and Michaely (2005), CFOs show strong preference for dividend stability, even laying off a large portion of workers and borrowing heavily before cutting dividends. In contrast to the findings in this paper, Guiso et al. (2005) find that firms insure their workers' wages against idiosyncratic shocks in productivity. Their analysis differs from our study in that they analyze firms that are larger than the firms in our sample. In addition, the nature of the shock to firm level sales is not clearly idiosyncratic in our setting since all hotels in the local economy are hit by snow shocks.

The literature distinguishes temporary and persistent shocks. Similar to the results in this study, it has been shown that firms provide more insurance to their workers against temporary shocks than against persistent shocks (see Gamber (1988), Guiso et al. (2005), Guertzgen (2014), Ellul et al. (2018)). In contrast to these studies, our research design allows us to use two "natural" counterparts[7] of the rather technical definitions of temporary and persistent shocks. [8]

The degree of insurance differs among different groups of firms. For example, using an international data set on listed firms, Ellul et al. (2018) show that family firms do provide more employment insurance to their employees in return for less wage insurance and a lower average wage. Despite the firms in our sample most likely being family firms[9], we find that firms share risk with their workforce.

Second, the paper is connected to the literature on relationship lending. Information creation by the repeated lending transactions between the same bank and borrower combination can help to overcome adverse selection and moral hazard problems that arise when banks lend to small and informationally opaque borrowers (see Stiglitz and Weiss (1981), Diamond (1984)). Boot (2000) claims that relationship lending enables the borrower and the lender to form a long-term implicit contract. This shifts the objective of the house bank from pure short-term profitability to a more long-term perspective. This increases the willingness to either renegotiate the terms of a loan or providing new capital to the borrower when she is in financial trouble due to a temporary negative shock (see Boot, Greenbaum, and Thakor (1993)). Elsas and Krahnen (1998) empirically show that house-banks provide liquidity insurance

[7] For an explanation of our measures of temporary and persistent shocks, see 3

[8] One side result in the related working paper of Baumgartner et al. (2020) is that firms share contemporaneous snow risk with their employees by adjusting employment as a result of shocks to snow only in the ending weeks of the winter season, i.e. the period in which negative shocks to sales become persistent.

[9] for a discussion, see section 2.2.

to their long term customers. As the duration of the lending relationship increases, borrowers face lower interest rates and collateral requirements (Boot and Thakor (1994)). Therefore, small firms, which are often very opaque, tend to borrow from a small number of lenders only; and the lending relationship between them is enduring (see Petersen and Rajan (1994)).

Throughout the lending relation, banks are able to acquire an informational advantage over competing banks. An advantage that is lost once the borrower goes into bankruptcy or the borrower enters into lending relationships with multiple lenders.

Petersen and Rajan (1995) analyze the effect of bank competition on relationship lending. They find that relationship lending is more prevalent in more concentrated banking markets, since it is less likely that a borrower enters into multiple lending relationships, i.e. the lender loses her informational advantage. In contrast, Boot and Thakor (2000) demonstrate that banks engage more in relationship lending activity once competition among banks increases. The idea is the following: As relationship lending is a specialized service which helps banks to insulate themselves from pure price competition in the transactions lending market.

Giroud et al. (2011) analyze a related data set: The subset of the customers of the Austrian Hotel and Tourism Bank (AHTB) which are in financial distress and undergo debt restructuring. They find that the AHTB grants debt forgiveness for ski hotels experiencing a debt overhang problem in order to restore the borrowers' incentives. In their study they do not find the AHTB to forgive debt for ski hotels which ended up in financial trouble caused by a series of negative snow shocks. We find a similar result for debt forgiveness. In addition, however, we find evidence suggesting that the AHTB is willing to adjust borrowers' interest payments as a result of negative snow shocks.

Third, the paper is connected to another strand of the literature that analyzes the role of the firms' suppliers as suppliers of credit to the firms. Petersen and Rajan (1997) find that firms use more trade credit when credit from banks is unavailable. They argue that, similar to relationship lenders, suppliers may have an comparative advantage in generating private information about the quality of their borrowers. At the same time, they also hold an implicit equity stake in their customers, by profiting from potential future sales to them. Similar results are found by Demirguc-Kunt and Maksimovic (2001) and Fisman and Love (2003).

2 Institutional background

2.1 The Austrian Hotel and Tourism Bank

All firms in our analysis are clients of the Austrian Hotel and Tourism Bank (AHTB). The AHTB was initially founded in 1947 as part of the Marshall Plan to reconstruct post World War 2 Europe, and its focus is on stimulating the tourism industry by provision of traditional banking services, which includes subsidized loans. Typically, the Austrian Tourism Bank's targets pivotal hotels in the local economy; therefore, the firms in our sample are larger than the average Austrian hotel.[10] We focus on hotels in the 10 kilometer radius around ski resorts, this represents about 17.5% of firms on the bank's client list.

2.2 The Austrian hotel industry

The hotels in our sample are likely to be family-owned firms, as family-owned firms make up for 93% of all firms in the industry.Doerflinger et al. (2013) While there are some hotel chains in urban areas, these firms are not contained in

[10] Data about the size of hotels is contained in Statistik Austria (2018). At the end of our sample period in 2006, the average Austrian hotel business had an accommodation capacity of 17.9 beds. The firms in our sample had an average accommodation capacity of 94.5 (median 80) beds.

our sample because we focus on hotel firms in ski resorts and exclude firms in towns with a population larger than 20,000.[11]

Given the size of our hotels, it is highly unlikely that they place a bond or issue public equity. As relatively small and family-owned firms, the firms in our sample depend mostly on bank debt as source of outside financing. If the firms receive outside equity, it is typically from relatives.[12] Hotels can use their buildings and land as collateral when borrowing from banks.

According to a report of the Austrian Ministry of Economy, the median leverage of Austrian three-star hotels was 119 % in the year 2003, while higher-quality hotels featured a leverage of 102 %.[13] These numbers are based on book values which allow for negative equity.

As firms in ski resorts, the firms in our sample cater to tourists whose demand depends on the snow conditions in the resorts. During our sample period, the hotels had limited ability to financially or operationally hedge the risk of a shortage in snow. To the best of our knowledge, there were no insurance products available, with which hotels could have insured the risk of a bad winter.[14] The most popular way how ski resorts manage their exposure to weather risk is by creating artificial snow. However, the prevalence of snow cannons during our sample period was very low. In fact, according to an Austrian newspaper report (see Salzburger Nachrichten (2015)), in 2007, one year after the end of our sample period, there existed less snow cannons in entire Europe than there did in three Austrian ski resorts alone in 2015[15]. In

[11] The alpine regions in Austria are only sparsely populated: e.g. the size of 20,000 will in Tyrol only exclude the capital city Innsbruck.

[12] Loans from relatives are also treated as equity investments under Austrian bankruptcy law.

[13] We report numbers for the year 2003 since this year is contained in our sample period (ending in 2006).

[14] Likewise, according to survey data from 2006 weather derivatives were primarily used by energy companies.Barrieu and Scaillet (2010)

[15] About 3,100 in 2007 versus 3,146 in 2015. The ski resorts are Ischgl (1,100), Wilder Kaiser (1,359), and Planai (690)

total there existed about 19,000 snow cannons in Austria in 2015. Töglhofer, Eigner, and Prettenthaler (2011) analyze panel data about 185 Austrian ski resorts and find that an unexpected change in snow conditions by one standard deviation changes the number of tourists' overnight stays in nearby hotels by 0.6-1.9%. In subsection 5.2.1, we find even stronger results for the firms in our sample. The cancellation policies for bookings at Austrian hotels are fixed in nationwide, industry-standard booking contracts. As a consequence, data about natural snow levels can be used as a measure for touristic demand.

Ski hotels employ a large fraction of seasonal employees throughout the winter season. Baumgartner et al. (2020) show that the average firm in the Austrian tourism industry, the share of seasonal employees is about 50% during the main part of the winter season. The employees often come from far away and are not customers of the firm. Most hotels in Austria use industry standard labor contracts. In these contracts, the notice period for layoffs is 2 weeks. The wage schemes in these contracts do not contain bonus pay or stock options.

3 Research strategy

We analyze to what extent firms share sales risk with their stakeholders by adjusting the contemporaneous payment to their stakeholders. The stakeholders we analyze are their banks, workers, suppliers, and landlords. For example, if firms are hit by an adverse sales shock, they might react by (i) laying off workers, or (ii) renegotiating terms of the loans with their banks. In both examples, we would observe a positive correlation between realized sales and the payments from the firms to their stakeholders, in the example their workers and the house-banks. Technically, we measure the sensitivity of firm i's payments to its stakeholders with respect to changes in sales. Consider the following regression equation:

$$p^s_{i,t} = \beta \; Sales_{it} + \gamma \; X_t + \alpha_i + \alpha_t + \epsilon_{i,t} \tag{1}$$

where $p^s_{i,t}$ denotes the payment from firm i to stakeholder s in period t. X_t denotes a vector of firm level control variables and α_i (α_t) denotes firm (year) fixed effects. β is defined as the change (in Euros) in the payment directed to stakeholder s given a 1 Euro increase in firm level sales. A β equal to zero would indicate that stakeholders are isolated from variation in sales and therefore do not bear firm level sales risk. In contrast, a positive estimate for β would be consistent with risk-sharing, i.e. firm i adjusting its payments to stakeholder s conditional on its sales. However, β in 1 only measures the correlation between the two variables and does not allow us to make a causal statement about the causal effect of sales on the payments to the stakeholders. Consider the following example for loan related payments to banks. If firm i enlarged the capacity of its hotel from one year to another and financed this expansion via a bank loan, we would expect to see (i) increased repayments and interests because of the loan, and (ii) higher sales as a result of the increased capacity. Therefore, our OLS analysis is subject to the concern of reverse causality.[16]

We make use of the fact, that the firms in our sample are subject to an exogenous source of variation in sales: Snow. As explained more in more detail in subsection 2.2, snow shifts tourists' demand for ski hotels' services. At the same time, snowfall is a natural event, which is plausibly not influenced by any firm level policy.[17] It is also plausible that snow has no direct effect on firms' payments to the stakeholders other than through firms' sales. For example, industry standard labor contracts do not include wage payments to

[16] Similar arguments can be made with the firm's wage bill, its trade credits, and its rent.
[17] Note that, as explained in 2, at the time of our analysis the creation of artificial snow was not as widely spread as it is today.

be contingent to the annual snow realization. Likewise, anecdotal evidence suggests that the predetermined payments related to loan contracts are not conditional on snow. We use snow[18] as an instrumental variable for sales in our regressions. In a standard two stage least squares specification, we first regress sales on snow:

$$Sales_{i,t} = b\ Snow_{j(m),t} + g\ X_t + a_i + e_{i,t} \tag{2}$$

and use the prediction of sales, $\widehat{Sales}_{i,t}$ as regressor in the second stage regression:

$$p^s_{i,t} = \beta'\ \widehat{Sales}_{i,t} + \gamma'\ X_t + \alpha'_i + \epsilon_{i,t}. \tag{3}$$

The β' coefficient estimated from equation 3 is the counterpart of β estimated from 1. However, it is not a pure correlation but it allows for causal interpretation of the sensitivity of stakeholders' cash flows to changes in firm level sales. The coefficient b in the first stage measures the average exposure of sales to snow risk. If hotels were able to operationally hedge snow risk perfectly by the use of artificial snow, b would be indistinguishable from zero, and we would have the problem of a weak instrument. If, however, hotels are exposed to snow risk, b is larger than zero.

As $Snow_{j(m),t}$ varies only on the level of the ski resort j which is closest to the municipality m of hotel i, we allow the residuals in our regressions to be correlated with each other in the same ski resort, i.e. we cluster the standard errors on ski resort level.

Focusing on ski hotels and using snow to instrument for sales has an interesting feature. Instead of being reliant on the popular but rather technical method

[18] As defined in equation 10

suggested by Guiso et al. (2005) to distinguish between temporary and persistent shocks to firm level sales, our research design enables us to use two empirical counterparts of temporary and persistent shocks to *within-season* sales. A lack of snow at the beginning of a winter season can be considered temporary, as snow is very likely to fall throughout the winter season. In contrast, adverse snow shocks at the late part of the winter season have a rather permanent effect: as spring comes closer, snow fall gets less likely. We use both snow in the early part and in the late part[19] of the winter season as instruments for sales in separate regressions. Results from the previous literature suggest, that hotels provide more insurance to their workers against temporary shocks than against persistent shocks.

We test four main hypotheses. First, we empirically test the statement of Knight (1921) from the beginning of the paper. If the notion of Knight (1921) prevails, first, we expect the sensitivity β'_e to be positive and significant for regressions of contemporaneous dividend payouts on sales, and, second, we expect workers to be isolated from sales shocks, i,e. $\beta'_w = 0$.

Second, as our hotels are highly dependent on bank debt and are small and opaque, we expect them to be in a lending relation with their house-bank. We test the predictions of Boot (2000) and Boot et al. (1993), suggesting that banks are willing to renegotiate existing loans in lending relationships when the borrowers are hit by temporary negative sales shocks.[20] If this is the case, we expect the hotel to be able to share the sales risk with their banks. Therefore, we expect the $\beta'_b > 0$ for loan related payments.

Third, we test whether hotels share sales risk with their suppliers via the provision of trade credit. Petersen and Rajan (1997) argue that, similar to re-

[19] Defined by equations 11 and 12

[20] Note that the duration of snow shocks is limited to one winter season. The permanent negative shocks in the ending weeks of the winter season are only permanent *within* the winter season.

lationship lenders, suppliers may have an comparative advantage in generating private information about the quality of their borrowers. At the same time, their objective is more long-term oriented, because they profit from potential future sales. If suppliers take on part of the firms' sales risk, we expect a $\beta'_{tc} > 0$.

Fourth, a similar argument can be made for the suppliers of land, i.e. the hotels' landlords. If hotels are able to share sales risk with their landlords by adjusting their rental payments, we expect to find $\beta'_{L} > 0$.

4 Data

4.1 Data sources

Firm level data is retrieved from the Austrian Tourism Bank (AHTB)[21]. Our complete data set contains the full set of this bank's clients between 1999 and 2012.[22] In total, we observe hotels' annual reports, containing the balance sheets and profit and loss statements, for 4,684 firms in the Austrian tourism sector. The hotels report book values, market values are not available as the firms in our sample are all in privately owned.

We use weather data for the years 1973 to 2006. The data come from the Austrian Meteorological Office (AMO) and cover the entire area of Austria. The AMO provides 1×1 km grid data containing daily information on snow depth, based on a snow cover model using air temperature and precipitation data (Beck, Hiebl, Koch, Potzmann, and Schöner (2009)). In order to measure the snow conditions in ski resorts, we use the coordinates of all ski lifts in Austria from OpenStreetMap, and calculate the average snow coverage of all lifts within a radius of 10 kilometers for each ski resort. For our snow data, the definition of a year deviates from that of a calendar year. To not tear apart a

[21] For more information on the Austrian Tourism Bank please see the subsection 2.
[22] We drop the year 1999, because the data coverage for this year is very low.

winter season, we define "season-year" t to start with the first of November of calendar year $t-1$ and end with the 31^{st} of October in calendar year t.

The balance sheet data and snow data are matched using the 5 digit official municipality key. We match the firm level balance sheets in calendar year t with snow data of "season-year" t. We have no information on the reporting date of the hotels in our sample. Anecdotal evidence suggests that the ski hotels rarely break the winter season into two parts by reporting at the end of the calendar year. Our results on the effect of snow on firm level sales suggest the same. The magnitude of the effect of snow in early period of the winter season, i.e. in months November and December of calendar year $t-1$, on sales is comparable to the effect of snow over the whole winter season t on sales. Out of 4,684 hotels, we select 818 hotels which are located within a 10 kilometer radius around one of Austria's 264 ski resorts.[23] For these firms, we construct an (unbalanced) firm-year panel data set containing the balance sheet information and snow data.

We exclude firm-years which display an unusual pattern in sales growth, i.e. observations for which the absolute value of the annual growth rate in sales is higher than 80%. To ensure that the firms in our sample have comparable production functions, we further exclude firms which have ownership of their local ski lifts and firms which make the majority of their sales from food & beverages, i.e. firms which are primarily a restaurant. Furthermore, we exclude hotels in cities[24] because these hotels are more likely to belong to one of the bigger hotel chains, and demand in cities is likely to be driven by different factors than for the rest of our sample.

[23] As stated in 2, these firms tend to be larger than the average hotel in Austria.
[24] We define a town as city if the population exceeds 20,000 inhabitants. This may seem low, but in the state of Tirol this includes only the capital Innsbruck.

4.2 Definition of variables

4.2.1 Dependent variables

In order to measure the risk sharing between a hotel and its stakeholders, we define variables which proxy for the payment from the firm to its stakeholders.[25] Since all hotels in our sample are privately held, market values are not available.

To account for outliers, all firm level variables are winsorized at the 1% level at both tails of the distribution.

Banks. We define the payments made by the hotel to its dominant supplier of (outside) capital, banks.[26]. We try to capture the payments associated with bank loans and define $p^B_{i,t}$ as the difference in bank debt outstanding between the years $t-1$ and t, $\Delta L_{i,t}$, and add the hotel's total interest payments, $I_{i,t}$, as reported by the hotel in year t's profit and loss statement. That is:

$$p^B_{i,t} = -\Delta L_{i,t} + I_{i,t} = -\Delta L^{lt}_{i,t} - \Delta L^{st}_{i,t} + I_{i,t} \tag{4}$$

where $L^{st}_{i,t}$ and $L^{lt}_{i,t}$ denote a hotel's short-term bank debt outstanding and long-term bank debt outstanding, respectively. The negative value of the annual change in long (short) term bank debt outstanding is an aggregated measure of the repayment of long (short) term loans and the provision of new long (short) term loans. If p^B is positive, we interpret it as a net payment from the hotel to its banks. If the borrower is unable to meet the scheduled repayments of

[25] Data from the balance sheet give us annual snapshots from which we can estimate the flows between the hotels and the shareholders. Data containing more frequent reporting periods are not available.

[26] For a discussion of why hotels in our sample are unlikely to have other sources of outside finance, see 2.

the loan, the bank and the borrower typically enter into bilateral negotiation on the deferral of interests and repayments.[27]

Workers. Payments from hotels and their workers, $p^w_{i,t}$, are measured by the total wage bill reported in the hotels' balance sheets in period t. The variable is decomposed into its two components representing the intensive and extensive margin: the average wage and the average number of employees per year.

$$p^w_{i,t} = \text{Wage bill}_{i,t} = \text{Average wage}_{i,t} \times \text{\# of employees}_{i,t} \tag{5}$$

Variation in the average wage can be attributed to bonus pay or other performance related wage schemes.

Suppliers. Through the provision of trade credit, hotels' suppliers of material inputs and services have the ability to play a similar role to that of a bank. The trade credit related payments between hotels and them are defined as:

$$p^{tc}_{i,t} = -(\text{Trade Credit}_{i,t} - \text{Trade Credit}_{t-1}) \tag{6}$$

Negative values of p^{tc} indicate that the suppliers in sum provided additional trade credit to the hotel in period t. Positive values of p^{tc} mean that hotels' repayment of trade credit exceeded the borrowing from suppliers in period t.

Landlords. Although hotels typically own most of their buildings and land, the vast majority of them engage in some minor renting activity.[28] The payments from hotels to landlords, p^L, is the annual rental fee from hotels' profit and loss statements.

[27] By default, if a borrower cannot pay back her loan, the repayment is deferred for three months and the loan is prolonged for this period.
[28] The median firm has annual rental fees of 11,300 Euros.

Entrepreneurs. As the firms in our sample are all private, we are not able to observe payments directed to the firms' owners directly. Instead, we use a method standard in accounting (see Stickney, Weil, Schipper, and Francis (2009)) and calculate the payments from information stated on the banks' balance sheets. Dividends to hotels' owners are defined as the difference between net profits and the change in retained earnings from period t to $t+1$, that is:

$$p^e_{i,t} = \text{Net Profit}_{i,t} - \Delta\text{Retained Earnings}_{i,t+1} \tag{7}$$

$p^e_{i,t}$ measures the part of firms' annual profits which is not kept within the firm but paid out to the entrepreneurs.[29] This measure is limited in that it does not allow us to measure payouts to the entrepreneurs in the form of wages or perks.

In additional tests, we use an alternative measure of p^e by substituting the change in retained earnings in 7 with the change in equity, i.e.:

$$p^{e,alt}_{i,t} = \text{Net Profit}_{i,t} - \Delta\text{Equity}_{i,t+1} \tag{8}$$

We do this because the standard accounting measure of dividends does not capture capital flows from the entrepreneurs into the firms. However, it is interesting to see if the entrepreneurs inject capital into the company as a result of a sales shock. Our alternative measure would capture this.

[29] Note that in our sample, as hotels are privately held, share repurchases are not an option to transfer funds to the owners.

4.2.2 Sales & snow

Sales. Annual sales revenue is the main independent variable of interest. Sales is defined as:

$$Sales_{i,t} = \text{Sales}_{i,t}^{N} + \text{Sales}_{i,t}^{F\&B} \tag{9}$$

where $\text{Sales}_{i,t}^{N}$ and $\text{Sales}_{i,t}^{F\&B}$ denote sales generated by nights accommodation and food & beverage, respectively. In robustness checks which are reported in the Online Appendix, we use the annual quantity of services sold, i.e. the annual total number of nights accommodation, denoted by $Nights_{i,t}$.

Snow. We define a dummy variable which measures whether it was possible to ski within the specific resort during a given week. This "Snow Day" dummy equals one if the ski lift's average snow level exceeded 10 centimeters at the time of measurement. In our main analysis, we use the sum of this dummy variable over all days, d, of year t's winter season, $W_{i,t}$. We define the winter season as the period starting at the beginning of November and ending at the end of April.

$$Snow_{j(m),t} = \sum_{\forall d \in W_t} \text{Snow Day}_{j(m),d} \tag{10}$$

where $j(m)$ denotes ski resort j located the closest to municipality m. The maximum distance between a hotel and a ski resort is set to 10 kilometers. If the distance exceeds 10 kilometers the variable is missing and the firm drops out of the sample. In further analyses, we define two alternative versions of this variable covering the two off-season periods of the winter season, the early season and the late season.

$$Snow^{early}_{j(m),t} = \sum_{\forall d \in W^{early}_t} \text{Snow Day}_{j(m),d} \tag{11}$$

$$Snow^{late}_{j(m),t} = \sum_{\forall d \in W^{late}_t} \text{Snow Day}_{j(m),d} \tag{12}$$

The early period of the winter season, W^{early}_t, includes the months November and December and the late period of the winter season, W^{late}_t consists of the months March and April.

We define dummy variables which indicate whether a winter was particularly good or bad. Bad (good) winter is defined as a dummy variable equaling one, if the number of snow days, *Snow*, is at least 1.2 standard deviations lower (higher) than the mean of *Snow*, i.e.: $(Snow - \bar{Snow})/\sigma_{snow} < -1.2$, and zero else.

4.2.3 Control variables & variables determining sample splits

We use firm level control variables in some our regressions. Financial leverage, *Lev*, is defined as the ratio between total debt and total assets ($Lev_{i,t} = Totaldebt_{i,t}/Totalassets_{i,t}$). Capital expenditures, $CAPEX_{i,t}$, is defined as the sum of the annual change in PP&E[30] and period t's depreciation of hotels' assets ($CAPEX_{i,t} = \Delta PP\&E_{i,t} + Depreciation_{i,t}$). To control for hotels' profitability, we use the return on investment ($ROI_{i,t}$) as reported by the AHTB.

In section 7, we use dummy variables to split our sample according to hotels' (i) size, (ii) financial leverage, (iii) labor market tightness in their counties, and (iv) the competition among banks which surround them.

[30] PP&E stands for property, plant, and equipment.

We define small firms as a dummy variable which equals one if the hotel's average amount of total assets over the whole sample period is smaller than that of the median firm.

Similarly, we define high leverage as a dummy variable equaling one, if the average leverage ratio of the firm over the sample period lies in the top 25% of the distribution. This dummy variable should capture firms which are close to financial distress.

Our measure for bank level competition is the number of distinct banks[31] within the 10 kilometer radius around the hotel. We measure labor market tightness as the inverse of the unemployment rate in county c of hotel i, i.e. $LMT_{c(i),t} = 1 - \text{unemployment rate}_{c(i),t}$. For both variables, number of distinct banks and labor market tightness, we compute the hotels' average value over the years of our sample and define a dummy variable which splits the sample at the median.

4.3 Summary statistics

Table 1 reports summary statistics for the variables in our analysis. We split the overall standard deviation into a between and a within component. The between component reflects pure cross-sectional variation between the hotels in our sample. In contrast, the within component measures only the variation over time.

On average, the firms in our sample received more money from the banks than they paid to them. The flow related to long term and short term loans exhibit relatively high within standard deviation, suggesting that the hotels invested during the sample period and financed the investment via bank loans.[32] In-

[31] We treat banks which belong to one the same group (for example Sparkassen) as one bank, as they typically are not allowed to compete with each other.

[32] Consistent with this explanation, we find capital expenditures to be positive on average and displaying high within standard deviation.

terest payments on average equal about 7,1% of sales revenues.[33] The within variation is relatively low, when compared to the other components of p^b. Mean and standard deviation of trade credit seems comparable to the short term component of p^b. Dividends to owners account for about 55% of the total wage bill. The within standard deviation is a lot higher for dividends than it is for the wage bill.

On average, the hotels in our sample experience a little more than 133 snow days throughout the winter season. The within standard deviation accounts for about 16% of the average duration of the winter season. An average hotel has total assets of 3.2 million Euros. The majority of the variation in total assets is caused by variation between the hotels. Our firms are heavily indebted. The average firm has a book leverage of 110%. However, this is common for that industry as explained in section 2.2. The firms' ROI is about 7.3% on average and the average hotel is located in the vicinity of 5.6 different banks. The unemployment rate in the counties is 10.8% on average. To account for outliers, all firm level variables are winsorized at the 1% level at both tails of the distribution.

5 Results

We present our results in the following order: First, OLS regressions are presented in subsection 5.1 and, second, causal evidence from instrumental variables regressions is presented in subsection 5.2. In all regressions we allow residuals to be correlated in the same ski resort.

5.1 OLS results

Banks. Table 2 reports estimates of regression equation 1 for loan related payments to banks. In column 1 to 3, we regress p^B as defined in 4 on sales

[33] The average interest rate equals about 6% of debt outstanding.

and a set of control variables. The sensitivity of p^B with respect to within variation in sales, β, is positive and statistically significant. For every extra Euro in sales, our hotels pay 65 cents to their banks. The magnitude of β drops significantly when including firm-level controls. This makes sense as capital expenditures in the hotel industry can be assumed to be financed via (long term) loans, which is consistent with the negative estimates for the coefficient of $CAPEX$. We disentangle p_B in its three components and report the results from column 4 on. When controlling for firm level control variables, repayment of long term loans, ΔL^{lt}, is not correlated with sales. In contrast, we find a positive and significant β for short term loan repayments, ΔL^{st}, and interest payments, I. A one dollar decrease in sales is associated with a 15 (6.2) cents decrease in the repayment of short term loans (interest repayments). The magnitude of the coefficients is stable when controlling for year fixed effects and firm level control variables.

Workers. Columns 1 to 3 in table 3 report results indicating a statistically and economically significant relation between sales and the total wage payments to workers. As reported in column 1, a one dollar decrease in sales is associated with an approximate 24 cent drop in wage payments. This magnitude of the effect is relatively stable when controlling for firm level control variables and year fixed effects. The results in the remaining columns (4-9) suggest that both the number of workers, as well as, the average wage per worker correlate positively with sales. These results suggest that firms do not provide wage insurance (as in Guiso et al. (2005)) or employment insurance (as in Ellul et al. (2018)) to their employees.

Suppliers. The results in columns 1 to 3 of table 4 document a statistically and economically significant correlation between sales and the payments related to trade credit. As reported in column 1, a one dollar decrease in sales is associated with a 20 cent increase in trade credit. The magnitude of this effect is stable when controlling for firm level control variables and year fixed effects.

Landlords. Columns 4 to 6 of table 4 report results about the relation between sales and rents payed to landlords. We find a positive and statistically significant effect. The economic significance is rather low. This is not surprising, given that the average firm in our sample pays rental fees of about 28,000 Euros per year in total.

Entrepreneurs. In columns 7 to 9 of table 4, we report results regarding the relation between sales and the payouts to the firm's owners. As explained in 2.2, most of our firms are family firms and are owner-managed.[34] The results suggest that in good years dividends to owners are high, whereas in bad years, owners abstain from paying high dividends. The magnitude of the coefficient is economically significant, i.e. for every dollar of additional sales payouts to owners increase by about 25 cents (column 7). The magnitude of the coefficient is comparable to the sensitive the wage bill payments to sales (see 3). In the first three columns of table 1 in the Appendix, we run the same set of regressions for the alternative definition of p^e stated in 8 and find similar results.

5.2 IV estimation

Given the endogeneity of hotels' sales in the previous regressions, it is questionable what we can learn from the results reported in 5.1. In this subsection, we try to establish the causal relationship between changes in firm level sales the firms' payments to their stakeholders. First, we present a quasi first stage

[34] Note that the firms in our sample are private companies. Therefore, share repurchases are unlikely to happen at our firms.

of our in 5.2.1. Second, we show estimates of the second stage IV regressions in 5.2. Third, in 6 we report IV estimates for temporary and permanent shocks to sales. Fourth, we analyze if the payment sensitivity is stable among different sub-groups of our sample in 7.

5.2.1 Exposure to snow risk

In principle, hotels could hedge against snow risk. In section 2.2, we explain why we think that they were not able to perfectly do so during the time of our sample. In table 5, we test if hotels were exposed to snow risk empirically. Columns 1 and 2 of table 5 display the strong positive relationship between snow and sales in our sample. An additional day of snow increases the sales of our hotels by about 1,700 Euros. The results in column 3 show that the effect is primarily driven by decreases in sales during particularly bad winters[35]. This is plausible, since ski hotels have a maximum level of capacity which sets an upper bound to sales. Column 5 breaks down snow into its off-season components: early season and late season snow. The results suggest that the snow shocks exhibit a particularly strong effect on sales in the late season. A 10 day increase in snow days at the end of the season explains 18% of the within firm standard deviation of sales.

The results are essentially the same if we run the analyses for nights accommodation instead of sales.[36] All in all, the results in table 5 suggest, that hotels in our sample are exposed to weather risk, and that snow as an instrumental variable is relevant. Given that the firms in our sample are larger than the average firm in the industry and that larger firms are better able to operationally hedge weather risk[37], we expect the average relationship between snow and sales in the industry to be even larger.

[35] For the exact definition of good (bad) winter see section 4.
[36] An additional day of snow translates into an increase of nights accommodation by 17 nights.
[37] By offering alternatives to skiing. For example, a hotel could install a spa area.

5.2.2 Stakeholders' payments and sales

Banks. Table 6 reports estimates for the second stage regression as defined in 3 in which p^s equals payments to banks. Regarding the total payments to banks p^B, the estimate of the sensitivity payments to banks with respect to sales shrinks from 0.85 (OLS) to 0.26 in column 1. In column 2, we find similar β estimates for the instrumental variables regression and the OLS regression, when controlling for firm level control variables. For every additional Euro of *weather induced* sales, roughly 39 cents flow from the hotels to their banks. This effect is significant at the 10% confidence level. The sizable and negative estimate for $CAPEX$ suggests that hotels finance the majority of their investments via bank credit.

In columns 3 to 8, we report the results for separate regressions for the components of p^B. In columns 4, there is weak evidence that hotels use *weather induced* sales revenues to repay their long-term loans. The coefficient for β' is larger than its OLS counterpart, but it is measured imprecisely, and therefore insignificant. In contrast, payments related to short term bank debt are not exposed to weather induced shocks to hotels' sales. The estimate of β in columns 5 and 6 are significantly smaller than the estimates from OLS regressions. We can reject the exogeneity of sales[38] in the IV regression of $-\Delta L^{st}$ on sales in column 5. This allows to cautiously conclude that hotels do not finance liquidity shortages after bad winters by the use of short term bank debt.

In columns 7 and 8, we report results of the sensitivity of hotels' interest payments to their snow induced sales. The magnitude of the sensitivity increases by more than 40% when changing from OLS to instrumental variables estimation. A one Euro decrease in sales leads to a reduction of interest payments by about 8.5 cents in column 8. This suggests that to some extent, banks allow

[38] We use the standard "difference-in-Sargan" test provided by STATA's ivreg2 command.

their customers to adjust the interest payments dependent on the realization of snow during the winter season.

We find evidence that hotels share sales risk with their house banks especially by adjusting their interest payments after exogenous sales shocks. One channel of liquidity provision by house-banks, is the use of credit lines. Using aggregated data, we cannot directly observe credit lines, but the pattern of our results regarding $-\Delta L^{st}$ and interest payments does not point to the use of credit lines to manage liquidity shortages after bad winters.[39] Extreme snow realizations could foster people's beliefs that the parameters of the distribution of snow are changing. This could affect hotels' investment behavior. For example, after good winters, hotels might be tempted to expand their capacity. Typically, an expansion like this would be financed via long term bank debt. If this channel dominates, we would expect to see a negative relation between weather induced sales and p^B but we find the opposite result.

Workers. In table 7, we report results regarding the causal effect of sales on hotels' payments to their employees. Reported in columns 1 and 2, a one Euro decrease in sales causes the wage bill to fall by about 21 cents. The estimates of β in the IV regressions are roughly 10 percent smaller when compared to OLS estimates. The results in columns 3 and 4 suggest, that firms share exogeneous sales risk with their workers by not hiring or firing them. A 100,000 decrease in sales revenues leads to the firing of one employee. In contrast, workers' annual wages are not sensitive to shocks in hotels' sales.[40] These results suggest that firms share weather induced sales risk with their workers via the extensive margin.

[39] We would expect interest payments and $-\Delta L^{st}$ to be negatively related to snow induced shocks.

[40] This is consistent with the previous results in the literature (see for example Guiso et al. (2005)).

Suppliers & landlords. The results in columns 1 and 2 of table 8 indicating no risk sharing of sales risk between hotels and their suppliers in the form of trade credit. The sensitivity is not statistically significantly different from zero and the magnitude of the sensitivity is reduces by half compared to the OLS results. Similar results are found for suppliers: Rental fees are not sensitive to weather induced sales shocks (see columns 3 and 4 of table of table 8).

Entrepreneurs. Surprisingly, in columns 5 and 6 of table 8, we do not find the sensitivity of p^e to sales to be statistically significantly different from zero. That means, the payments to the hotels' owners are not systematically exposed to exogenous changes in hotels' sales caused by snow. Note that the size of the coefficient does not shrink significantly[41] but the standard errors increase. This is unlikely to be caused by weak identification, as the F-statistic in the first stage regression is high. Also, inflating standard errors in the IV analysis is not a problem when regressing payments to workers, p^w, on sales in table 7.

This suggests that if the firms' entrepreneurs bear sales risk, they do so in other ways than by adjusting their contemporaneous payouts to them.[42] This result is limited because we cannot observe directly wages and perks directed to the owner-managers of our firms. An alternative explanation for our findings could be that hotels' owner-managers chose to pay themselves higher wages instead of paying out profits in the form of dividends. However, in table 7 we do not find the average wage in hotels to be sensitive to weather induced sales. Perks are not observable given our data.

In the last two columns of table 1 in the Appendix, we run the same set of regressions for the alternative definition of p^e stated in 8 and find comparable results. With this alternative definition, we are able to identify whether owners

[41] A test for the endogeneity of $Sales$ cannot be rejected.

[42] Note that the firms in our sample are typically non-listed family firms and do not payout cash to their owners in the form of share repurchases.

inject capital as a response to a bad winter. However, we do not find evidence that this is the case, instead the results are relatively close to the results stated in table 8.

Results. To sum up the IV results - we find quite the opposite of the hypothesis of Knight (1921). Entrepreneurs seem not to bear sales risk but there is evidence suggesting that workers do. In addition, our results suggest that entrepreneurs seem to able to share the sales risk with their house-banks by adjusting the interest payments. We do not find evidence for the sharing of sales risk between the hotels their suppliers and landlords.

Concerning the problem of weak instrumentation in out IV regressions, the F-Test statistics[43] of the significance of the excluded instruments in the first stage regressions ranges from 26.2 to 38.2 and, hence, lie above the classical "rule of thumb" threshold of 10 as suggested by Staiger and Stock (1997) or the criteria suggested by Stock and Yogo (2005). Therefore, as suggested by the results in subsection 5.2.1, snow is not a weak instrument in our IV regressions.

6 Temporary versus persistent sales shocks

We analyze whether hotels' risk sharing with their workers and their house banks depends on the persistence of the sales shock. By nature, snow induced sales shocks are not persistent from one winter season to another. However, we can distinguish between persistent and temporary sales shocks *within* the winter season. During the starting weeks of the winter season, negative snow shocks are temporary because additional snow is likely to fall in the following weeks. In contrast, negative snow shocks that happen at the end of the winter season are rather persistent. Once snow has melted at the end of the season,

[43] We report the Cragg-Donald F-statistic.

new snow fall becomes less likely as spring gets closer. Instead of using the total number of snow days in as an instrumental variable, we separately use the number of snow days in the early season and the late season (as defined in equations 11 and 12) to estimate equation 2.

Workers. Given that ski hotels employ a high fraction of seasonal workers and given the findings of Guiso et al. (2005), we expect hotels to provide more insurance to workers against temporary than against persistent *within-season* sales shocks. In table 10 we present the results for regressions of the total wage bill on firm level sales. In columns 1, 3, and 5, we report the results of the first stage regressions (see equation 2). As in our previous analysis, we use the total number of snow days in column 1. In column 3 (5), we instrument sales by snow days in the early (late) period of the winter season, i.e. sales shocks which are temporary (permanent). We present the results of the second stage regressions of our different instrumentation strategies in columns 2, 4, and 6. As previously shown in 7, we find workers not to be sheltered from weather induced sales shocks in column 2. However, our result in column 4 suggests that firms are insuring their workers against sales risk caused by snow shocks in the early season, i.e. against temporary shocks. As reported in column 6, the risk sharing between hotels and their workers happens at the end of the winter season when weather induced sales shocks are persistent. This result is not driven by imprecise measurement of the effect during the early part of the season. The magnitude of the coefficient of early snow in the first stage is comparable with that of total snow. The F-Test statistic suggest that early snow does not seem to be a weak instrument. However, the magnitude of β in the second stage shrinks by half when instrumenting by early snow, instead of total snow. The findings are consistent with the previous literature (see Guiso et al. (2005), Ellul et al. (2018)).

Banks. After analyzing the wage bill to workers, we turn to the risk sharing between firms and banks via the adjustment of interest payments. Baumgartner et al. (2020) find that banks' capitalization has an effect on entrepreneurs' risk taking behavior in the early period of the winter season. Using the same framework as in the previous paragraph, we analyze the relationship between hotels' annual interest payments and weather induced sales shocks. The estimates in table 9 suggest that hotels do indeed share sales risk with their house-banks during the late period of the winter season (as well as during the early period); a result consistent with the findings in Baumgartner et al. (2020). We do not find a difference in risk sharing between hotels and their house banks for temporary and persistent *within-season* sales shocks. Hotels are able to share both kinds of shocks with their house-banks. This is not surprising, as the duration of the lending relationship is very likely to exceed one winter season and, therefore, persistent *within-season* sales shocks are still considered temporary by the hotels' house-banks.

7 Cross-sectional variation in β

In this subsection, we analyze how the effect measured in subsection 5.2 varies within different subgroups of our sample. We focus on those stakeholders, for which we found a positive and significant sensitivity of payment to sales in subsection 5.2.2: banks and workers. We perform the sample split on size because there can be differences in the bargaining power to renegotiate wages or defer interest payments between smaller and larger firms. Similar to the family firm argument in Ellul et al. (2018), smaller firms might be better able to credibly commit to provide their employees with employment insurance.

Workers. We split the sample according to the hotels' size, financial leverage, and the labor market tightness of the surrounding county. Given the short time horizon of our sample, all variables which determine the sample splits are time-invariant, i.e. firms do not switch between the sub samples over time.[44] Table 11 reports results of separate IV second stage regression performed on each sub-sample. The results in column 1 and 2 show that the sensitivity of hotels' wage bill to changes in sales is both positive and significant for small and large firms. The magnitude of the coefficient is lower for small firms. In table 2 in the Appendix we show that the difference between the coefficients for small and large hotels in a reduced form regression is statistically significant. This finding is consistent with the notion of small, family owned businesses being better able to credibly grant employment insurance to their workers (see Ellul et al. (2018)).

Columns 3 and 4 of table 11 show that firms in financial trouble are not able to share weather induced sales risk with their workers.[45] Reduced form estimates reported in table 2 in the Appendix support this result. Given that we do not find wage insurance, one explanation for this finding is that high leverage firms are not able to adjust their employment as other firms because they are left with only the key employees, probably mostly family members.[46] The remaining workforce is not taking snow induced sales out of the firms in the form of wages, a result consistent with the interpretation of the wage result in Giroud et al. (2011).[47]

Columns 5 and 6 of table 11 report results of a sample split according to the labor market tightness[48] of the hotel's county. We find that hotels share sales risk in counties that display high labor market tightness. The difference between the coefficients for high and low labor market tightness is significant in the reduced form regression reported in table 2 in the Appendix. In counties

[44] For an exact definition of the variables, see 4.

[45] Note that we have a week identification problem in the regression producing the results of column 4.

[46] In unreported tests, we find that high leverage firms are in fact more than 30% smaller and pay significantly lower wages than other firms.

[47] The authors interpret low wages as owners' willingness to keep cash in the firm.

[48] Labor market tightness is defined as the inverse of the unemployment rate in the hotel's county. For an exact definition, see 4

with high labor market tightness it should be easy for workers to find new employment. Thus, employment insurance might not be important for workers in these counties.[49]

Banks. Table 12 report similar tests for hotels' interest payments. The coefficients do not vary when splitting the sample according to firm size in column 1 and 2. We find a difference when splitting according to financial leverage: Firms with high levels of leverage seem not to be able to adjust their interest payments as a reaction to weather induced sales.[50] This result is consistent with the result of Giroud et al. (2011) who analyze firms that undergo debt restructuring with the AHTB. They find that banks are willing to renegotiate terms only to restore managers' incentives, but not after the hotel has experienced adverse snow shocks.

In column 5 and 6 of table 12 we study how the risk sharing between firms and their house-banks is influenced by competition on the bank level. There exist two opposing theories: Petersen and Rajan (1995) predict that relationship lending is less prevalent in markets with high levels of bank competition, whereas the model of Boot and Thakor (2000) predicts the opposite. We split our sample based on the number of competing banks in the vicinity of the hotels and test the loan related payments in the subgroups are affected by sales. If the theory of Petersen and Rajan (1995) prevails, we expect $\beta_b' > 0$ for the sub sample of hotels in low competition banking markets, and β_b' indistinguishable from zero in the sub sample of hotels in high competition banking markets. The opposite pattern in results would lend support to the theory of Boot and Thakor (2000).

[49] We find wages in these counties to be 3.8% higher than in other counties. The evidence is weak as the difference is not statistically significant.
[50] We find the parameters to be significantly different in the reduced form specification reported in table 2 in the Appendix.

Hotels are better able to share sales risk with their banks in areas that exhibit high competition among banks.[51] The difference between the parameters is found to be significant in the reduced form specification reported in table 2 in the Appendix. This finding empirically supports the theory of Boot and Thakor (2000), which predicts that banks engage more in relationship lending activity when the level of bank competition is high.

8 Conclusion

In this paper, we empirically derive that firms do not insure their workers against sales risk. This finding contradicts the view of Knight (1921). Our results indicate that entrepreneurs are able to share sales risk with their workers using the extensive margin, i.e. adjusting their workforce. In addition, our results suggest that entrepreneurs share sales risk with their banks by adjusting their interest payments after exogenous sales shocks. One very interesting result is that bank level competition seems to increase the degree of risk sharing the bank is willing to accept. This finding is an empirical counterpart of the theory of Boot and Thakor (2000). Entrepreneurs seem to demonstrate their advanced ability in managing risk. In particular, by sharing sales risk with their stakeholders, their contemporaneous dividend payouts are isolated from exogenous sales shocks.

Our choice of sample allows us to use snow risk as an exogenous source of sales risk. We propose a new method for distinguishing between temporary and persistent shocks, which depends on the timing of the sales shock within the winter season. Our results on the provision of employment insurance is consistent with the existing literature. The ski hotel industry is small and exceptional but it shares many properties with other, more larger and more important industries like construction or agriculture. The firms are small, bank

[51] Bank competition is defined as the number of banks within the 10 kilometers radius around the hotel. For an exact definition, see 4

dependent, demand for their products or services exhibits high cyclicality, and they are exposed to weather risk. Due to climate change, weather risk is expected to increase in the future and therefore represents a globally severe challenge for firms in exposed industries. Our findings are therefore relevant to understand and predict the consequences of climate change on unemployment and the health of local banking markets. Weather risk is a systematic risk in local banking markets and therefore constitutes a cluster risk for local banks.

References

Azariadis, C. (1975). Implicit contracts and underemployment equilibria. *Journal of Political Economy 83*(6), 1183–1202.

Barrieu, P. and O. Scaillet (2010). *Weather Derivatives.* American Cancer Society.

Baumgartner, S., T. Schober, A. Stomper, and R. Winter-Ebmer (2020). Weather risk and employment: Banking on snow. Working Paper.

Beck, A., J. Hiebl, E. Koch, R. Potzmann, and W. Schöner (2009). Institutionelle und regulatorische Fragestellungen der Bereitstellung von Wetterdaten. *Graz: Economics of Weather and Climate Risks Working Paper Series* (10).

Boot, A. (2000). Relationship banking: What do we know? *Journal of Financial Intermediation 9*(1), 7–25.

Boot, A., S. I. Greenbaum, and A. Thakor (1993). Reputation and discretion in financial contracting. *American Economic Review 83*(5), 1165–83.

Boot, A. and A. Thakor (1994). Moral hazard and secured lending in an infinitely repeated credit market game. *International Economic Review 35*(4), 899–920.

Boot, A. and A. Thakor (2000). Can relationship banking survive competition? *The Journal of Finance 55.*

Brav, A., J. R. Graham, C. Harvey, and R. Michaely (2005). Payout policy in the 21st century. *Journal of Financial Economics 77*(3), 483–527.

Brown, P. B. (2013). *Hate Risk? You Could Be The Perfect Entrepreneur.* https://www.forbes.com/sites/actiontrumpseverything/2013/09/

01/hate-risk-you-could-be-the-perfect-entrepreneur, (Accessed: 2020-05-15).

Demirguc-Kunt, A. and V. Maksimovic (2001, October). Firms as financial intermediaries - evidence from trade credit data. Policy Research Working Paper Series 2696, The World Bank.

Diamond, D. W. (1984, 07). Financial Intermediation and Delegated Monitoring. *The Review of Economic Studies 51*(3), 393–414.

Doerflinger, C., A. Doerflinger, K. Gavac, and B. Vogl (2013). *Familienunternehmen in Oesterreich*. KMU Forschung Austria.

Ellul, A., M. Pagano, and F. Schivardi (2018). Employment and wage insurance within firms: Worldwide evidence. *The Review of Financial Studies 31*(4), 1298–1340.

Elsas, R. and J. P. Krahnen (1998). Is relationship lending special? evidence from credit-file data in germany. *Journal of Banking & Finance 22*(10-11), 1283–1316.

Farrell, D. and C. Wheat (2019). The Small Business Sector in Urban America. https://institute.jpmorganchase.com/content/dam/jpmc/jpmorgan-chase-and-co/institute/pdf/institute-small-business-sector-report.pdf, (Accessed: 2020-05-17).

Fisman, R. and I. Love (2003). Trade credit, financial intermediary development, and industry growth. *The Journal of Finance 58*(1), 353–374.

Gamber, E. N. (1988). Long-term risk-sharing wage contracts in an economy subject to permanent and temporary shocks. *Journal of Labor Economics 6*(1), 83–99.

Giroud, X., H. M. Mueller, A. Stomper, and A. Westerkamp (2011). Snow and Leverage. *The Review of Financial Studies 25*(3), 680–710.

Guertzgen, N. (2014). Wage insurance within German firms: Do institutions matter? *Journal of the Royal Statistical Society: Series A (Statistics in Society) 177*(2), 345–369.

Guiso, L., L. Pistaferri, and F. Schivardi (2005). Insurance within the firm. *Journal of Political Economy 113*(5), 1054–1087.

Herranz, N., S. Krasa, and A. P. Villamil (2015). Entrepreneurs, risk aversion, and dynamic firms. *Journal of Political Economy 123*(5), 1133–1176.

Kihlstrom, R. E. and J.-J. Laffont (1979). A general equilibrium entrepreneurial theory of firm formation based on risk aversion. *Journal of Political Economy 87*(4), 719–48.

Knight, F. H. (1921). Risk, uncertainty and profit, 1921. *Library of Economics and Liberty*.

Moskowitz, T. J. and A. Vissing-Jorgensen (2002, September). The returns to entrepreneurial investment: A private equity premium puzzle? *American Economic Review 92*(4), 745–778.

Petersen, M. and R. Rajan (1997). Trade credit: Theories and evidence. *Review of Financial Studies 10*(3), 661–91.

Petersen, M. A. and R. Rajan (1995). The effect of credit market competition on lending relationships. *The Quarterly Journal of Economics 110*(2), 407–443.

Petersen, M. A. and R. G. Rajan (1994). The benefits of lending relationships: Evidence from small business data. *The Journal of Finance 49*(1), 3–37.

Rettl, D., A. Stomper, and J. Zechner (2019). The stability of dividends and wages: Effects of competitor flexibility. CFS Frankfurt Working Paper 549.

Salzburger Nachrichten (2015). *Beschneiungsanlagen*. https://www.sn.at/wiki/Beschneiungsanlage, (Accessed: 2020-05-10).

Staiger, D. and J. H. Stock (1997, May). Instrumental Variables Regression with Weak Instruments. *Econometrica 65*(3), 557–586.

Statistik Austria (2018). Bestandsstatistik Tourismus. STATcube - Statistische Datenbank von STATISTIK AUSTRIA. [accessed 2018-Sep-4].

Stickney, C., R. Weil, K. Schipper, and J. Francis (2009). *Financial Accounting: An Introduction to Concepts, Methods and Uses*. Cengage Learning.

Stiglitz, J. E. and A. Weiss (1981, June). Credit Rationing in Markets with Imperfect Information. *American Economic Review 71*(3), 393–410.

Stock, J. and M. Yogo (2005). *Testing for Weak Instruments in Linear IV Regression*, pp. 80–108. New York: Cambridge University Press.

Stulz, R. and R. G. Williamsom (1996). Identifying and quantifying exposures. Research in financial economics, Ohio State University.

Töglhofer, C., F. Eigner, and F. Prettenthaler (2011). Impacts of snow conditions on tourism demand in Austrian ski areas. *Climate Research 46*(1), 1–14.

U.S. Census Bureau (2015). Statistics of U.S. Businesses. https://www.census.gov/programs-surveys/susb/data/tables.2015.html, (Accessed: 2020-05-17).

U.S. Small Business Administration (2018). Small business profile. https://www.sba.gov/sites/default/files/advocacy/2018-Small-Business-Profiles-US.pdf, (Accessed: 2020-05-17).

Tables

Table 1: Summary statistics

This table reports the mean, the standard deviation, the minimum, the maximum and the number of observations for the variables of interest. The data set has a hotel-year panel structure. We split the overall standard deviation into a between and a within component. The between component reflects pure cross-sectional variation between the hotels in our sample. We winsorize 1% on both ends of the distribution for all continuous variables.

Variable	Category	Mean	SD	Min	Max	Obs
p^B (in TEUR)	overall	-58	949.8	-16586.4	5626.8	2565
	between		404.3			593
	within		866.8			4.3
-ΔL^{LT} (in TEUR)	overall	-132.8	805.9	-11903.1	5188	2565
	between		376.4			593
	within		718.8			4.3
-ΔL^{ST} (in TEUR)	overall	-25.3	510.3	-5139.2	4908.7	2565
	between		150.9			593
	within		488.9			4.3
I (in TEUR)	overall	100	110	.9	1132.7	2565
	between		102.1			593
	within		41.4			4.3
p^w (in TEUR)	overall	321.6	424.7	6.5	4487	2516
	between		417.3			534
	within		92.9			4.7
# of workers	overall	23.8	24.3	2	198	2477
	between		24.4			533
	within		4.2			4.6
Average wage (in TEUR)	overall	13.5	9.8	0.4	209.1	2477
	between		8.5			533
	within		3.7			4.6
p^L (in TEUR)	overall	27.9	64.1	0	1158.9	3184
	between		55.1			593
	within		32.3			5.4
p^{tc} (in TEUR)	overall	-2.9	251.8	-2472.3	2430.6	2565
	between		65.3			593
	within		243.9			4.3
p^e (in TEUR)	overall	178.2	622.8	-4289.1	5888.6	3083
	between		565.6			593
	within		324.1			5.2
Sales (in TEUR)	overall	1409.3	1421.5	72.6	9799.7	3184
	between		1433.3			593
	within		255.4			5.4
Snow	overall	133.5	33.8	0	182	3184
	between		26.6			593
	within		21.2			5.4
Total Assets (in TEUR)	overall	3171.2	4081.3	57.4	46097.8	3181
	between		4096.6			593
	within		1060.3			5.4
CAPEX (in TEUR)	overall	399.5	929	-385.8	8985.9	3184
	between		525.5			593
	within		770.7			5.4
Leverage	overall	110	57.7	5.8	431.8	3181
	between		54.1			593
	within		21.8			5.4
ROI	overall	7.3	8	-30.5	51.2	3184
	between		5.9			593
	within		5.5			5.4
# of Banks	overall	5.6	1.7	2	10	3184
	between		1.7			593
	within		.4			5.4
Unemployment Rate	overall	10.8	2.2	6	15	3179
	between		2.1			593
	within		.5			5.4

Table 2: OLS: Risk sharing between hotels and banks.

This table reports estimates of regression equation 1 for hotels' loan related payments to banks. In column 1 to 3, we regress p^B (as defined in equation 4) on sales and a set of firm level control variables. For a definition of the firm level variables, see 4. We disentangle p_B into its three components and report the results from column 4 to column 12. $-\Delta L^{lt}$ ($-\Delta L^{st}$) denotes an hotel's payment to its banks which is associated with long term (short term) bank loans loans. I denotes a hotel's interest payment. For a discussion of the table see 5.1. All regressions include hotel fixed effects. Year fixed effects are added in column 3, 6, 9, and 12. We winsorize 1% on both ends of the distribution for all continuous variables. Standard errors are clustered at the ski resort level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	p^B			$-\Delta L^{lt}$			$-\Delta L^{st}$			I		
Sales	0.849***	0.405***	0.443***	0.392*	0.0700	0.0703	0.396***	0.272***	0.311***	0.0612***	0.0632***	0.0624***
	(0.264)	(0.128)	(0.143)	(0.224)	(0.129)	(0.144)	(0.103)	(0.0953)	(0.106)	(0.0136)	(0.0138)	(0.0149)
Leverage		-3697.4***	-3811.9***		-3291.1***	-3313.1***		-425.6	-518.4*		19.35	19.65
		(990.7)	(1009.8)		(945.5)	(944.5)		(270.0)	(290.4)		(37.97)	(36.21)
ROI		8788.3***	7739.6***		8561.5***	8459.6***		556.0	-375.9		-329.2	-344.1
		(2538.4)	(2780.0)		(2335.7)	(2619.0)		(1673.1)	(1790.1)		(301.7)	(327.2)
CAPEX		-0.898***	-0.895***		-0.638***	-0.637***		-0.263***	-0.261***		0.00308*	0.00319*
		(0.0645)	(0.0638)		(0.0544)	(0.0539)		(0.0345)	(0.0335)		(0.00166)	(0.00167)
N	2565	2562	2562	2565	2562	2562	2565	2562	2562	2565	2562	2562
AdjR2	0.06	0.67	0.67	0.02	0.47	0.47	0.04	0.20	0.20	0.13	0.13	0.15
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES

Table 3: OLS: Risk sharing between hotels and their workers

This table reports estimates of regression equation 1 for hotels' payments to their workers, p^w. In column 1 to 3, we regress the hotels' total wage bill on sales and a set of firm level control variables. For a definition of the firm level variables, see 4. We disentangle the wage bill into its two components: the number of workers (columns 4-6) and the average wage (columns 7-9). For a discussion of the table see 5.1. All regressions include hotel fixed effects. Year fixed effects are added in column 3, 6, and 9. We winsorize 1% on both ends of the distribution for all continuous variables. Standard errors are clustered at the ski resort level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	p^w			# of workers			Average wage		
Sales	0.237***	0.240***	0.234***	0.00000620***	0.00000645***	0.00000611***	0.00216***	0.00210***	0.00183***
	(0.0180)	(0.0185)	(0.0185)	(0.00000102)	(0.00000111)	(0.00000120)	(0.000317)	(0.000323)	(0.000354)
Leverage		49.81	61.94		0.00529	0.00555*		0.406	0.788
		(56.31)	(57.39)		(0.00321)	(0.00308)		(3.771)	(3.832)
ROI		-638.0	-487.9		-0.0249	-0.0163		-11.48	-7.050
		(586.0)	(612.3)		(0.0183)	(0.0187)		(26.34)	(23.64)
CAPEX		0.00436	0.00420		0.000000512**	0.000000504**		-0.000209	-0.000215
		(0.00715)	(0.00714)		(0.000000230)	(0.000000223)		(0.000212)	(0.000214)
N	2516	2514	2514	2477	2475	2475	2477	2475	2475
AdjR2	0.40	0.41	0.41	0.14	0.15	0.15	0.01	0.01	0.01
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	YES	NO	NO	YES	NO	NO	YES

Table 4: OLS: Risk sharing between hotels and other stakeholders

This table reports estimates of regression equation 1 for hotels' change in trade credit p^{tc}, (column 1 to 3), their rental fee p^{L}, (column 4 to 6), and the payouts to their owners p^{e}, (7-9). We regress these variables on firm level sales and a set of firm level control variables. For a definition of the firm level variables, see 4. For a discussion of the table see 5.1. All regressions include hotel fixed effects. Year fixed effects are added in column 3, 6, and 9. We winsorize 1% on both ends of the distribution for all continuous variables. Standard errors are clustered at the ski resort level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	p^{tc}			p^{L}			p^{e}		
$Sales$	0.200***	0.142***	0.160***	0.0145***	0.0149***	0.0167***	0.252***	0.233***	0.199***
	(0.0568)	(0.0534)	(0.0609)	(0.00520)	(0.00533)	(0.00628)	(0.0436)	(0.0415)	(0.0424)
$Leverage$		-175.0	-229.9		16.57	13.77		-856.6***	-773.3***
		(144.1)	(155.1)		(23.29)	(23.02)		(299.3)	(288.7)
ROI		-731.9	-1201.5		-415.6	-459.0		7678.5***	8361.4***
		(923.7)	(1012.8)		(438.6)	(479.7)		(1019.3)	(1077.9)
$CAPEX$		-0.125***	-0.123***		-0.000643	-0.000648		-0.0177	-0.0187
		(0.0165)	(0.0161)		(0.00111)	(0.00109)		(0.0122)	(0.0119)
N	2565	2562	2562	3184	3181	3181	3083	3080	3080
AdjR2	0.04	0.18	0.18	0.01	0.02	0.02	0.12	0.18	0.19
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	YES	NO	NO	YES	NO	NO	YES

Table 5: Snow and firm level demand

This table reports results on regressions of firm level sales on snow realizations. The results Columns 1 and 2 document the strong positive relationship between snow and sales in our sample, with and without firm level control variables. The results in column 3 show that the effect is primarily driven by decreases in sales during particularly bad winter, but not by good winters. Bad (good) winter is defined as a dummy equaling one, if the number of snow days, *Snow*, is at least 1.2 standard deviations lower (higher) than the mean of *Snow*, and zero else. Column 5 breaks down snow into its off-season components: early season and late season snow. For a precise definition of the variables, see 4. We winsorize 1% on both ends of the distribution for all continuous variables. Standard errors are clustered at the ski resort level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	Sales				Nights			
$Snow$	1724.0***	1732.5***			17.14***	17.05***		
	(323.8)	(315.0)			(4.025)	(3.942)		
Good winter			11381.4				263.2	
			(21662.7)				(231.5)	
Bad winter			-67539.2***				-551.9***	
			(22856.4)				(194.0)	
$Snow^{early}$				909.3**				13.17***
				(375.9)				(4.193)
$Snow^{late}$				4238.9***				35.49***
				(660.2)				(8.458)
$Leverage$		-721.0***	-704.4***	-701.0***		-9.321***	-9.121***	-9.139***
		(161.2)	(169.6)	(159.9)		(2.872)	(2.886)	(2.883)
ROI		2392.2**	2232.7**	2534.8**		3.421	2.145	4.215
		(1084.2)	(1077.0)	(1082.4)		(13.00)	(12.99)	(12.89)
$CAPEX$		-0.0289	-0.0300*	-0.0293		-0.000548**	-0.000557***	-0.000551***
		(0.0178)	(0.0180)	(0.0179)		(0.000211)	(0.000212)	(0.000211)
N	3184	3181	3181	3181	3158	3155	3155	3155
AdjR2	0.02	0.03	0.02	0.04	0.01	0.03	0.02	0.03
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	NO	NO	NO	NO

Table 6: IV: Risk sharing between hotels and banks.

This table reports estimates of instrumental variables regressions (as defined in equation 3) for hotels' loan related payments to banks. In column 1 and 2, we regress p^B (as defined in equation 4) on sales and a set of firm level control variables. For a definition of the firm level variables, see 4. We disentangle p_B into its three components and report the results from column 3 to column 8. $-\Delta L^{lt}$ ($-\Delta L^{st}$) denotes an hotel's payment to its banks which is associated with long term (short term) bank loans loans. I denotes a hotel's interest payment. For a discussion of the table see 5.2.2. At the bottom of the table, we report the F-Test statistic of the excluded instruments in the first stage regression, and we report the p-value of a Durbin-Wu-Hausman test for endogeneity of *Sales*. All regressions include hotel fixed effects. We winsorize 1% on both ends of the distribution for all continuous variables. Standard errors are clustered at the ski resort level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	2^{nd} Stage							
	p^B		$-\Delta L^{lt}$		$-\Delta L^{st}$		I	
Sales	0.256	0.398*	0.256	0.359	-0.0874	-0.0452	0.0872***	0.0846***
	(0.419)	(0.228)	(0.389)	(0.250)	(0.248)	(0.242)	(0.0187)	(0.0181)
Leverage		-3700.8***		-3135.2***		-596.5*		30.90
		(978.2)		(978.2)		(305.8)		(37.00)
ROI		8803.4***		7878.0***		1305.3		-379.8
		(2497.1)		(2393.2)		(1789.0)		(287.8)
CAPEX		-0.898***		-0.625***		-0.277***		0.00404*
		(0.0671)		(0.0545)		(0.0391)		(0.00211)
N	2565	2562	2565	2562	2565	2562	2565	2562
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	NO	NO	NO	NO
1st stage F-Test	35.58	38.22	35.58	38.22	35.58	38.22	35.58	38.22
Endogeneity test (p-value)	0.17	0.98	0.71	0.27	0.08	0.23	0.23	0.32

Table 7: IV: Risk sharing between hotels and workers.

This table reports estimates of instrumental variables regressions (as defined in equation 3) for hotels' payments to their workers, p^w. In column 1 and 2, we regress the hotels' total wage bill on sales and a set of firm level control variables. For a definition of the firm level variables, see 4. We disentangle the wage bill into its two components: the number of workers (columns 3 and 4) and the average wage (columns 5 and 6). For a discussion of the table see 5.2.2. At the bottom of the table, we report the F-Test statistic of the excluded instruments in the first stage regression, and we report the p-value of a Durbin-Wu-Hausman test for endogeneity of *Sales*. All regressions include hotel fixed effects. We winsorize 1% on both ends of the distribution for all continuous variables. Standard errors are clustered at the ski resort level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	2^{nd} Stage					
	p^w		# of workers		Average wage	
Sales	0.217***	0.214***	0.0000101***	0.00000982***	0.00136	0.00142
	(0.0344)	(0.0343)	(0.00000176)	(0.00000171)	(0.00234)	(0.00226)
Leverage		38.95		0.00711**		0.0388
		(58.08)		(0.00327)		(3.781)
ROI		-557.2		-0.0358		-9.286
		(616.6)		(0.0219)		(29.49)
CAPEX		0.00343		0.000000638***		-0.000234
		(0.00623)		(0.000000228)		(0.000200)
N	2486	2484	2447	2445	2447	2445
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	NO	NO
1st stage F-Test	31.26	34.12	31.26	33.56	31.26	33.56
Endogeneity test (p-value)	0.60	0.52	0.08	0.13	0.72	0.75

Table 8: IV: Risk sharing between hotels and other stakeholders.

This table reports estimates of instrumental variables regressions (as defined in equation 3) for hotels' change in trade credit (column 1 and 2), their rental fee (column 3 and 4), and the payouts to their owners (5 and 6). We regress these variables on firm level sales and a set of firm level control variables. For a definition of the firm level variables, see 4. For a discussion of the table see 5.2.2. At the bottom of the table, we report the F-Test statistic of the excluded instruments in the first stage regression, and we report the p-value of a Durbin-Wu-Hausman test for endogeneity of *Sales*. All regressions include hotel fixed effects. We winsorize 1% on both ends of the distribution for all continuous variables. Standard errors are clustered at the ski resort level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	2^{nd} Stage					
	p^{tc}		p^L		p^e	
$Sales$	0.101	0.113	-0.0000674	-0.00143	0.144	0.163
	(0.109)	(0.108)	(0.0147)	(0.0151)	(0.141)	(0.128)
$Leverage$		-190.5		4.466		-919.7***
		(145.0)		(23.34)		(353.2)
ROI		-663.7		-379.6		7830.2***
		(947.3)		(425.0)		(1036.9)
$CAPEX$		-0.126***		-0.00112		-0.0197
		(0.0175)		(0.00125)		(0.0130)
N	2565	2562	3184	3181	3083	3080
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	NO	NO
Firm-level controls	NO	YES	NO	YES	NO	YES
1st stage F-Test	35.58	38.22	28.36	30.25	26.16	27.93
Endogeneity test (p-value)	0.45	0.82	0.28	0.24	0.40	0.55

Table 9: Disentangling sales shocks. Risk sharing with workers.

This table reports estimates of instrumental variables regressions for hotels' payments to their workers, p^w. Columns 1, 3, and 5 report results of the first stage regression 2. In column 1, we use total snow as defined in 10. In column 2 (3) we use snow days in the early (late) part of the winter season as defined in 11 (12). Adverse snow shocks are temporary (persistent) if they happen at the beginning (end) of the winter season. Columns 2, 4, and 6 report results for the second stage regressions as defined in equation 3. For a discussion of the results, see 6. At the bottom of the table, we report the F-Test statistic of the excluded instruments in the first stage regression, and we report the p-value of a Durbin-Wu-Hausman test for endogeneity of *Sales*. All regressions include hotel fixed effects. We winsorize 1% on both ends of the distribution for all continuous variables. Standard errors are clustered at the ski resort level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	Full		Early		Late	
	Sales	p^w	Sales	p^w	Sales	p^w
$Sales$		0.217***		0.0982		0.268***
		(0.0344)		(0.0647)		(0.0285)
$Snow$	2137.1***					
	(377.5)					
$Snow^{early}$			1981.8***			
			(415.3)			
$Snow^{late}$					5459.8***	
					(901.1)	
N	2486	2486	2486	2486	2486	2486
Firm FE		YES		YES		YES
Year FE		NO		NO		NO
1st stage F-Test	32.04		22.78		36.71	
Endogeneity test (p-value)		0.60		0.03		0.33

Table 10: Disentangling sales shocks. Risk sharing with workers.

This table reports estimates of instrumental variables regressions for hotels' interest payments to their banks, I. Columns 1, 3, and 5 report results of the first stage regression 2. In column 1, we use total snow as defined in 10. In column 2 (3) we use snow days in the early (late) part of the winter season as defined in 11 (12). Adverse snow shocks are temporary (persistent) if they happen at the beginning (end) of the winter season. Columns 2, 4, and 6 report results for the second stage regressions as defined in equation 3. For a discussion of the results, see 6. At the bottom of the table, we report the F-Test statistic of the excluded instruments in the first stage regression, and we report the p-value of a Durbin-Wu-Hausman test for endogeneity of *Sales*. All regressions include hotel fixed effects. We winsorize 1% on both ends of the distribution for all continuous variables. Standard errors are clustered at the ski resort level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	Full		Early		Late	
	Sales	I	Sales	I	Sales	I
$Sales$		0.0872***		0.0795***		0.0796***
		(0.0187)		(0.0308)		(0.0207)
$Snow$	2146.6***					
	(359.9)					
$Snow^{early}$			1879.4***			
			(387.3)			
$Snow^{late}$					5872.5***	
					(859.5)	
N	2565	2565	2565	2565	2565	2565
Firm FE		YES		YES		YES
Year FE		NO		NO		NO
1st stage F-Test	35.58		23.55		46.68	
Endogeneity test (p-value)		0.23		0.59		0.37

Table 11: Sample splits: Risk sharing with workers.

This table reports estimates of instrumental variables regressions (as defined in equation 3) for hotels' wage payments to their workers, p^w. In columns 1 and 2, we report results for separate regressions on the subset of smaller and larger firms (compared to the median firm). In columns 3 and 4, we report results for separate regressions on the subset of firms with moderate and high levels of financial leverage (Firms in the top 25% bracket of the distribution of leverage are classified as *High*). In columns 5 and 6, we report results for separate regressions on the subsets of counties with low and high labor market tightness (LMT). We split the counties at the median. All dummy variables which are used to split the sample are computed by using average values and therefore time invariant. For a definition of the variables, see 4. For a discussion of the results, see 7. At the bottom of the table, we report the F-Test statistic of the excluded instruments in the first stage regression, and we report the p-value of a Durbin-Wu-Hausman test for endogeneity of *Sales*. All regressions include hotel fixed effects. We winsorize 1% on both ends of the distribution for all continuous variables. Standard errors are clustered at the ski resort level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	p^w					
	Firm size		Leverage		LMT	
	Small	Large	Low	High	Low	High
Sales	0.173***	0.225***	0.231***	-0.0264	0.0977	0.262***
	(0.0557)	(0.0382)	(0.0338)	(0.241)	(0.103)	(0.0317)
N	1013	1473	1880	606	1350	1136
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	NO	NO
1st stage F-Test	10.51	25.71	32.76	3.42	7.82	24.21

Table 12: Sample splits: Risk sharing with banks.

This table reports estimates of instrumental variables regressions (as defined in equation 3) for hotels' interest payments to their banks, I. In columns 1 and 2, we report results for separate regressions on the subsets of smaller and larger firms (compared to the median firm). In columns 3 and 4, we report results for separate regressions on the subsets of firms with moderate and high levels of financial leverage (Firms in the top 25% bracket of the distribution of leverage are classified as $High$). In columns 5 and 6, we report results for separate regressions on the subsets of hotels with high and low level of competition in the banking market (we split at the median). All dummy variables which are used to split the sample are computed by using average values and therefore time invariant. For a definition of the variables, see 4. For a discussion of the results, see 7. At the bottom of the table, we report the F-Test statistic of the excluded instruments in the first stage regression, and we report the p-value of a Durbin-Wu-Hausman test for endogeneity of $Sales$. All regressions include hotel fixed effects. We winsorize 1% on both ends of the distribution for all continuous variables. Standard errors are clustered at the ski resort level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	I					
	Firm size		Leverage		# of Banks	
	Small	Large	Low lev	High lev	Low	High
$Sales$	0.0837***	0.0879***	0.101***	-0.0756	0.0497	0.108***
	(0.0250)	(0.0212)	(0.0190)	(0.0816)	(0.0352)	(0.0239)
N	990	1575	1977	588	1398	1167
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	NO	NO
1st stage F-Test	12.71	28.61	34.75	6.62	9.48	31.90

Appendix

Table 1: OLS & IV: Alternative definition of payouts to owners

This table reports estimates of OLS regressions (column 1 to 3) and instrumental variables regressions (column 4 and 5) for the alternative definition of the payouts to hotels' owners, p^e_{alt}, as defined in equation 8. We regress these payouts on firm level sales and a set of firm level control variables. For a definition of the firm level variables, see 4. For a discussion of the table see 5.2.2. At the bottom of the table, we report the F-Test statistic of the excluded instruments in the first stage regression, and we report the p-value of a Durbin-Wu-Hausman test for endogeneity of *Sales*. All regressions include hotel fixed effects. We winsorize 1% on both ends of the distribution for all continuous variables. Standard errors are clustered at the ski resort level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	$p^{e,alt}$				
	OLS			IV	
Sales	0.277***	0.257***	0.215***	0.239	0.262
	(0.0659)	(0.0644)	(0.0680)	(0.223)	(0.213)
Leverage		-1010.2**	-881.4**		-1005.5**
		(441.4)	(425.5)		(495.7)
ROI		9431.7***	10170.2***		9420.4***
		(1340.6)	(1524.3)		(1431.0)
CAPEX		-0.0129	-0.0149		-0.0127
		(0.0160)	(0.0157)		(0.0179)
N	3083	3080	3080	3083	3080
Firm FE	YES	YES	YES	YES	YES
Year FE	NO	NO	YES	NO	NO
1st stage F-Test				26.16	27.93
Endogeneity test (p-value)				0.86	0.98

Table 2: Reduced form: Testing for differences in coefficients.

This table reports estimates of reduced form regressions of hotels' wage bills, p^w, and their interest payments to their house-banks, I, on *Snow*. In columns 1 and 4, we interact *Snow* with the dummy variable Large, which equals one if the firm is larger than the median firm, and zero else. In columns 2 and 5, we interact *Snow* with a dummy variable indicating if the hotel has a high financial leverage. Firms in the top 25% bracket of the distribution of leverage are classified as High Leverage. In column 3, we interact *Snow* with a dummy variable for the local labor market tightness, LMT. In column 6, we interact *Snow* with a dummy indicating a high level of competition in the local banking market. All regressions include hotel fixed effects. We winsorize 1% on both ends of the distribution for all continuous variables. Standard errors are clustered at the ski resort level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	p^w			I		
Snow	125.9***	625.5***	145.8	69.85***	258.8***	82.41
	(45.66)	(146.0)	(184.1)	(20.20)	(52.64)	(69.28)
Snow × Large	617.1***			199.3**		
	(205.4)			(76.87)		
Snow × High Leverage		-637.3***			-312.2***	
		(172.2)			(67.75)	
Snow × High LMT			522.3**			
			(235.6)			
Snow × High # of Banks						195.6**
						(88.82)
N	2516	2516	2516	2565	2565	2565
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	NO	NO

Interbank Lending and Banks' Supply of Liquidity Insurance to the Real Sector

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June 2020

Abstract

We analyze interbank lending using a sample of banks in Austrian ski resorts. The banks are subject to liquidity shocks due to weather-induced demand shocks in ski tourism. We analyze the effect of these shocks on interbank lending and borrowing. The analysis reveals that banks reduce their net lending to other banks at times when they need to provide liquidity to their customers. Our evidence adds to the literature regarding the role of the interbank market in banks' liquidity creation. It highlights effects of a specific type of liquidity creation, i.e., the liquidity insurance banks provide to the real sector. We find that shocks triggering this insurance reduce banks' longer-term lending to other banks, but we find no effects on short-term net lending. Moreover, we observe particularly strong effects on banks with regionally focused operations, banks with higher equity ratios, banks that face relatively low levels of snow risk, and banks with a geographically diversified branch network.

1 Introduction

The market for interbank lending is key to ensuring the liquidity of banks when they need to respond to shocks affecting their non-bank counterparties. Paravasini (2008), Khwaja and Mian (2008), Schnabl (2012) and follow-up papers document the real effects of disruptions to interbank liquidity provision. Iyer, Lopes, Peydro, and Schoar (2014) show that the unexpected freeze of the European interbank market in August 2007 caused a credit supply shock affecting small, entrepreneurial firms.

This paper analyses interbank lending based on a view of banks as suppliers of liquidity insurance to firms outside the financial sector (Holmstrom and Tirole (1998), Kashyap, Rajan, and Stein (2002)). Is the provision of this liquidity insurance associated with interbank liquidity provision? If individual banks represent "local pools of liquidity" (Holmstrom and Tirole (1998)), are these pools linked to each other through the market for interbank lending?

To answer these questions, we use a two-step research strategy based on liquidity shocks caused by weather risk, i.e., shocks that occur for exogenous reasons. We first test whether this risk affects banks as a cause of liquidity shocks associated with the liquidity insurance they provide to households and firms in the real economy. This sets the stage for the next step of the analysis in which we test whether interbank lending also responds to the liquidity shocks. To the best of our knowledge, we provide the first evidence regarding the role of the interbank market in facilitating liquidity insurance that banks offer to customers outside the financial sector.

Our analysis is based on a sample of Austrian banks with a readily identifiable exposure to weather risk since they are located close to ski resorts. The banks operate in regional economies dominated by tourism businesses which are exposed to frequent demand shocks resulting from changes in the ski resorts' snow conditions. These demand shocks are clearly unrelated to the banks' ability to inject liquidity into the surrounding economy because most tourists come to the ski resorts from other countries or, at least, other parts of Austria. Instead, the demand shocks cause liquidity shocks in tourism businesses. Our analysis traces how these liquidity shocks affect the banks and the interbank market.

In the first part of our analysis, we simply document the liquidity shocks. We test whether the banks' deposits fluctuate with the number of tourists visiting the ski resorts. This test is based on annual data and instrumental variables regressions in which we use variation in snow conditions to instrument tourists' overnight stays in the resorts. Bank deposits could be correlated with the tourists' overnight stays for reasons other than weather-induced demand shocks.[1] We want to focus on these shocks because they are clearly unpredictable conditional on regional fixed effects.[2] While the weather conditions can be predicted a fews days ahead, this is often insufficient for tourism firms because their planning horizons are typically much longer. As a consequence, the firms are subject to liquidity shocks induced by weather risk, and these shocks may also affect the firms' deposits with local banks.[3]

We find that weather-induced variation in tourists' overnight stays causes significant variation in bank deposits. A one percentage point increase in tourists' overnight stays creates a 2.5 percentage points increase in deposits. In unre-

[1] In fact, there may also be some reverse causality. For example, tourists overnight stays may increase due to changes in hotels' prices, and hotels' pricing policies may depend on their capital structures and liquidity, including their cash held as bank deposits. For an analysis, see Pichler, Stomper, and Zulehner (2008) (who also use data about hotels in Austrian ski resorts).

[2] Given that we only have annual data about bank deposits, our estimates come from variation in snow conditions aggregated to the annual level. Snow conditions are clearly unpredictable a year ahead.

[3] For example, the firms must hire seasonal workers many weeks before the start of the skiing season because the workers must typically move to the ski resorts before they can start working. When the firms commit to employing these workers, they take the risk of liquidity shocks induced by weather risk as a risk of demand shocks. See Baumgartner, Schober, Stomper, and Winter-Ebmer (2020).

ported results, we also find similar variation in banks' loans to non-banks. This is not surprising because banks aim at adjusting their assets (loans) and liabilities (deposits). More interesting results come from regressions explaining the difference between loan and deposit growth. We refer to this difference as banks' liquidity provision to the real economy because it measures the extent of bank lending (positive growth of loans to non-banks) and paying out deposits (negative deposit growth). If the banks provide liquidity insurance to their customers, we should see that their liquidity provision responds to liquidity shocks hitting these customers. This is indeed what we find using liquidity shocks due to weather-induced variation in tourists' overnight stays. A one standard deviation decrease in tourists leads to an increase in net lending to non-bank customers by half a standard deviation.

Our first set of results sets the stage for the next part of our analysis in which we test whether the weather-induced variation in tourists' overnight stays also affects interbank lending. These tests have the same structure as those regarding banks' liquidity provision to non-bank customers, but we focus on interbank borrowing and lending. The main dependent variable is the difference between the growth rate of a bank's loans to other banks and that of the bank's loans from other banks. We refer to this difference as net interbank lending. If this interbank lending facilitates the liquidity insurance that banks provide to the real sector, we should observe that banks receive higher (net) loans from other banks at times when the banks' non-bank customers need liquidity injections. Put differently, interbank lending should be "crowded out" by banks' lending to (non-bank) customers. This is our main hypothesis.

We test the hypothesis by focusing on the weather-induced liquidity shocks to tourism business in Austrian ski resorts. We find that these shocks cause the local banks to borrow more from/lend less to other banks. This is consistent with our hypothesis. A further result comes from distinguishing between short-term and long-term loans that banks make to other banks.[4] We use our data about these loans in order to construct two versions of our dependent variable measuring net interbank lending, i.e., short-term and long-term net lending. The first variation is the difference between the growth rate of a bank's short-term loans to other banks and that of the bank's loans from other banks. The second variable is defined in a similar way, but for long-term loans.

We find that it is banks' long-term net lending to other banks that gets "crowded out" by their lending to non-bank customers, but short-term interbank lending is not significantly affected. This is consistent with the idea that the interbank market facilitates the liquidity insurance banks provide to (non-bank) customers.

While our estimates are about effects of tourism demand shocks, we can use them to compute a multiplier connecting the observed elasticities of banks' net lending to (non-bank) customers and net interbank lending. Given our point estimates for these elasticities, their ratio equals approximately 12, i.e. a one percentage point increase in net lending to non-bank customers is associated with a 12 percentage point decrease in net interbank lending. This is a take-away from our analysis that may generalize to other settings. We expect that interbank lending will respond in a similar way to liquidity shocks in other industries. Our evidence comes from an industry in which it is particularly easy to identify the liquidity shocks because firms in this industry have few alternatives to liquidity insurance provided by their banks.

The following section describes our research strategy. Section 3 describes the institutional background. Section 4 provides a description of the data. The baseline results are presented in section 5. In section 6, we test for cross-sectional differences in our baseline results. Section 7 concludes.

[4] Unfortunately, we cannot distinguish between short-term and long-term loans banks receive from other banks.

2 Research strategy

We use data about a sample of banks in Austrian municipalities close to ski resorts. We choose this sample because the banks operate in regional economies dominated by ski tourism as an industry whose assets have a readily identifiable physical location linked to specific weather risks. During our sample period, the industry faced repeated demand shocks associated with changing snow conditions in the ski resorts. Our research strategy is based on these demand shocks as a cause of liquidity shocks.

The inspiration for our analysis comes from Holmstrom and Tirole (1998) view of the financial system as a liquidity pool which redistributes liquidity between different parts of an economy. If this view is correct, we should see that the banks in ski resorts respond to liquidity shocks triggered by demand shocks due to unfavorable weather. In particular, we should see a decrease in bank deposits and/or an increase in loans as the banks' customers demand liquidity by either withdrawing deposits or applying for loans. The first alternative is actually more straightforward than the second because changes in deposits are mostly driven by depositors' decisions. In fact, it is possible that deposit outflows cause a reduction in credit supply at times when the demand for bank loans increases as firms seek to cope with liquidity shocks.[5] As a consequence, our main dependent variable will measure banks' overall liquidity provision to their customers. While we will also analyze deposit growth per se, our main regressions explain the difference between loan growth and deposit growth. By using this variable, we consider banks' net liquidity provision to their customers, either through positive loan growth or through negative deposit growth.

[5] In unreported regressions, we actually find that bank loans increase in (instrumented) bank deposits).

We will run the following regressions with fixed effects at the bank and year levels:

$$\text{Net lending}_{B,t} = \beta \times \Delta log(Tourists)_{B,t} + \alpha_B + \alpha_t + \epsilon_{B,t} \tag{1}$$

where the dependent variable is the difference between the loan growth and deposit growth of bank B in year t, and the main explanatory variable is the growth of tourists' overnight stays in the ski resorts where bank B's branches are located. For details regarding these variables, see the following section. The explanatory variable is a proxy for tourists' demand for accommodation and other services in the municipalities where bank B has branches. Of course, this variable will also vary for reasons other than weather-induced demand shocks. For example, there is a potential for reverse causality because hotels' pricing policies may depend on their liquidity needs. We can, however, safely assume that tourists' overnight stays are not directly linked to variation in bank deposits or loans because tourists typically demand no banking services other than ATMs. This implies that, by making sure that we identify shocks to tourists' demand for overnight stays, we will measure effects of these shocks on banks that exist due to the impact of the shocks on the finances of businesses and households close to the ski resorts.

We address the identification problem by using data about ski resorts' snow conditions in order to construct an instrumental variable. The construction of this variable will be described in detail in the following section. For now, it suffices to point out that the snow conditions are essentially unpredictable a year ahead so that our instrument really identifies shocks given that we use annual data. To interpret these shocks as liquidity shocks, we must, however, rule out that our instrument proxies for shocks to investment opportunities that could also affect bank deposits and loans. To weaken this identifying assumption, we use fixed effects as catch-all control variables. For example, our bank-level fixed effects should control for changes in investment opportunities due to climate change. In essence, we assume that the economic agents behind our data view weather risk as a risk of temporary shocks which mainly affect their liquidity needs, but contain no new information that could affect the agents' views of their investment opportunities.

Regressions similar to the above-stated one will be used to analyze interbank lending and borrowing. The dependent variable of these regressions is the difference between the growth rate of a bank B's loans to other banks and that of the banks loans from other banks. We refer to this difference as net interbank lending. We will test whether banks allow for their interbank lending to be "crowded out" by their liquidity provision to non-bank customers when these customers are affected by weather-induced liquidity shocks. In this case, we should observe that the regressions explaining net interbank lending differ from the above-stated regression in terms of the sign of the coefficient of (instrumented) tourists' overnight stays.

3 Institutional background

3.1 The Austrian hotel industry

Ski tourism is an important sector of the Austrian economy. According to Statistics Austria (2018) in 2017 the tourism industry accounted for 6.4% of the GDP directly and 15.3% of GDP indirectly[6]. Ski tourism is an especially important part of the Austrian Tourism industry. In the state of Tirol, a state famous for its many ski resorts, 17.5% of the GDP can be attributed to

[6] This calculation takes into account value added by the supply chains of the touristic firms which is not captured by the first statistic.

tourism. In contrast, in Upper Austria, a state with fewer ski resorts, only 4% of the GDP is created by tourism (see Tirol Tourism Research (2018)).

Tourism firms in ski resorts cater to tourists whose demand depends on the snow conditions in the resorts. Töglhofer, Eigner, and Prettenthaler (2011) analyze panel data about 185 Austrian ski resorts and find that an unexpected change in snow conditions by one standard deviation changes the number of tourists' overnight stays in nearby hotels by 0.6-1.9%. The typical firm in the Austrian tourism industry is a small and family owned hotel or restaurant. Doerflinger, Doerflinger, Gavac, and Vogl (2013) show that 93% of all firms in the tourism industry are family owned. Given the size of Austrian hotels, it is highly unlikely that they place a bond or issue public equity. As relatively small and family-owned firms, the firms in our sample depend mostly on bank debt as source of outside financing. If the firms receive outside equity, it is typically from relatives.[7] Hotels can use their buildings and land as collateral when borrowing from banks. These firms usually have long going banking relationships with a house-bank and depend heavily on the bank for all kinds of financial services.

Hotels have limited ability to financially hedge the risk of a shortage in snow. To the best of our knowledge, there were no insurance products available, with which hotels could have insured the risk of a bad winter.[8] The most popular way how ski resorts manage their exposure to weather risk is by creating artificial snow. The prevalence of snow cannons in Austria grew throughout our sample period. According to an Austrian newspaper report (see Salzburger Nachrichten (2015)), in 2007 there existed 3,100 snow cannons in entire Europe versus 19,000 snow cannons in Austria alone in 2015. However, there exist technical and legal limits for the production and use of artificial snow.

[7] Loans from relatives are also treated as equity investments under Austrian bankruptcy law.

[8] Likewise, according to survey data from 2006 weather derivatives were primarily used by energy companies.Barrieu and Scaillet (2010)

The time span in which artificial snow can be produced is legally restricted.[9] The production is particularly intensive in water and energy. Water is taken mainly from water reservoirs especially constructed to supply the snow cannons. The use of artificial snow is therefore costly for the ski resorts, which are usually owned by the municipalities connected to the ski resort and by a group of hotels located in the ski resort. Despite the legal and economical limits of artificial snow, its rise throughout our sample period might bias the estimates in our first stage regression of equation 1 towards zero, as the natural snow levels lose importance for tourists' ability to ski.

3.2 The Austrian banking industry

Like Germany, Austria has a "three-pillar" banking sector, consisting of private banks (stock corporations), savings banks, and cooperative banks. Throughout the paper, we refer to the latter two groups as "local banks". The groups of savings banks and cooperative banks operate within group-specific institutional frameworks, featuring joint supervisory institutions and deposit insurance, as well as lead banks that provide the groups with access to the wider financial markets. Within-group competition between banks is quite limited, but there is a healthy level of between-group competition. In terms of population size per bank branch, Austria remains among the most competitive countries in the European Union.[10] In terms of total assets, the savings banks have a market share of about 20% while the cooperative banks have a share of about 30% (Bülbül, Schmidt, and Schüwer (2014)).

In terms of ownership links, the groups of savings and cooperative banks are separate parts of the Austrian banking sector, but there are complex cross-ownership structures within the groups. The groups feature internal equity capital markets. For example, the savings banks' lead bank, Erste Bank, is

[9] In the state of Tirol, for example, ski resorts in low altitudes are allowed to use snow cannons from November until the end of March.
[10] See Table 9.2 in ECB (2017).

partly owned by other savings banks. The internal equity markets are also key to resolving cases of financial distress. Distressed banks are typically saved through mergers with other banks in the same group.

As in Germany, the banks within a group also assist each other in their lending, e.g., by making joint loans.[11] This practice complements the groups' internal equity markets. To avoid that a lack of equity capital constrains an individual bank's lending, the bank can either obtain equity capital from other banks in the same group or make a joint loan together with the other banks. In the latter case, the banks' joint equity capital must be sufficient in order to meet regulatory equity capital requirements. Throughout our sample period, the Austrian banks were subject to equity capital requirements according to Basel I until 2007 and Basel II after 2007.

The Austrian banking market is one of the most competitive banking markets in the European Union (see ECB (2017)). There exist a large number of small banks, many of which only operate on a regional level. This limits their ability to diversify regional risks by pooling clients from different regions. Hence, in general, regional shocks to the banks' clients should transmit to the banks and, more specifically, regional snow shocks should be visible at the bank level because touristic firms represent an important part of the local economy. Banks' deposits should vary with the financial strength of their clients. After a good winter the ski hotels' deposits at their banks should increase because they experienced a successful winter season. In contrast, after a bad winter, ski hotels are likely to withdraw funds from their deposit accounts in order to finance the losses they inquired throughout the winter season.

4 Data

[11] For further discussion with respect to German savings banks, see DSGV (2012).

Bank data. All Bank level data are retrieved from the Austrian National Bank (ANB). The final data set is constructed by combining two independent data sets on (i) the banks' branch networks and (ii) their annual statements. First, for branch network data, we have access to the full list of individual bank branches of Austrian banks for every year separately between the years 1998 to 2012. This data set comprises information on the location of the branches, and it contains the structure which links the individual branches to the banks. [12]

Second, we obtain the annual statements of all banks which operated in Austria between the years 1998 to 2016. The annual statements are reported on the website of the ANB, and contain all information from banks' balance sheets. The two data sets are merged using the banks' sort codes and the respective year. We use the structure of the branch network and aggregate the balance sheet data for all branches with different sort codes that belong to the same bank.

The final data set contains the universe of banks which operated in Austria between the years 1998 and 2012. Over the whole sample period, we observe 6,144 distinct bank branches which belong to 713 banks. As depicted in figure 1, both the number of banks and the number of branches display a similar trend over time. They peak in the beginning of the sample period in 1999 (banks) and 2002 (branches), followed by a decline thereafter.[13]

Tourism data. Data about tourism in Austria are obtained from Statistics Austria. Statistics Austria provides information on the number of tourists' arrivals in municipalities and the number of nights accommodation that tourists

[12] Note, that in Austria it is possible and common, that banks' branches operate using different bank sort codes.

[13] Note, however, that both numbers are still relatively stable over time. The difference between maximum and the minimum of the number of banks is less than 10% of the maximum number of banks.

stayed at hotels in a municipality. This data is separately reported for the winter season and the summer season.[14] We have tourism data for 1976 municipalities in Austria for the years 1972 to 2012.

Snow data. The Austrian Meteorological Office (AMO) reports weather data for each of their 131 weather stations throughout Austria. We obtain monthly data on the weather stations for the years from 1972 to 2013. For our snow data, the definition of a year deviates from that of a calendar year. To not tear apart a winter season, we define "season-year" t to start with the first of November of calendar year $t-1$ and end with the 31^{st} of October in calendar year t.

For each weather stations, we define a dummy variable which measures whether it was possible to ski on a given day. This "Snow Day" dummy equals one if the snow level exceeded 10 centimeters at the time of measurement, and zero else. The total number of snow days during the winter season, denoted Snow $\text{days}_{s,t}$, is defined as the sum of the "Snow Day" dummies for all days of the winter season, i.e. all days of the months November till April.

Using the snow data and the location of the weather stations, we construct a variable similar to Snow $\text{days}_{s,t}$ for every Austrian municipality. This variable is as a linear combination of snow data of the five weather stations, which are located the closest to the municipalities.

The information of these weather stations are not weighted equally. We assume that the closer the weather stations are located to the municipality, the more informative they are about the actual snow coverage in the municipality. Therefore, we weight the information of station s by $w_{m,s}$, which decreases as the distance between the weather station and the municipality $dist(s,m)$ in-

[14] The definition of the winter season used by the Austrian Statistics Office is the same as our definition of the winter season, i.e. the months from November till April.

creases. The weight is defined as $w_{m,s} = 1/dist(s,m)$.[15] We define the number of snow days in municipality m as:

$$\text{Snow days}_{m,t} = \sum_{s=1}^{5} \frac{w_{m,s}}{\Sigma_{s=1}^{5} w_{m,s}} \text{Snow days}_{s,t} \tag{2}$$

Matching the data. We use the information about the location of a Bank's branches and match the snow data and the tourism data of the respective locations to the branches. Subsequently, we aggregate the branch level information about tourism and snow to the bank level. We drop financial institutions from our sample, which do not share the business model of a consumer bank. These institutions include the Austrian National Bank, all institutions such as company pension funds in the "Sonderbanken" sector, and building societies. For a detailed description of the data match and the aggregation, see subsections 4.1.1 and 4.1.2. We end up with a bank-year panel data set covering 653 banks in Austria for the years 1999 until 2016.

4.1 Definition of variables

4.1.1 Bank level Tourism

We link the tourism data of municipality m to a bank's branch by using the official key of the municipality where the branch is located. We construct a bank-level measure of exposure to tourism by aggregating the snow data of all the municipalities in which bank B is active in year t, i.e. runs a branch. The variable is defined as:

[15] We make sure that there is no case in which $dist(s,m) = 0$

$$Tourists_{B,t} = \sum_{\forall m} I_{m,B,t}\text{Nights}^{w}_{m,t} \tag{3}$$

where $I_{m,B,t}$ is an indicator variable equaling one if bank B operates at least one branch in municipality m in year t and zero else. $\text{Nights}^{w}_{m,t}$ denotes the number of nights accommodation that tourists spend in municipality m during year t's winter season.

4.1.2 Bank level Snow

Similar to the construction of bank level tourism, we link the snow data of municipality m in year t's winter season to a bank's branch by using the official key of the municipality where the branch is located. We construct a measure of snow exposure of bank B by aggregating the snow data of all municipalities in which the bank operates branches in a given year t. Bank B's snow exposure is defined as:

$$Snow_{B,t} = \sum_{\forall m} I_{m,B,t}\text{Snow days}_{m,t} \tag{4}$$

$\text{Snow days}_{m,t}$ denotes the number of snow days in municipality m during year t's winter season as defined in equation 2.

4.1.3 Net lending

All dependent variables are constructed by data obtained from banks' balance sheets. For more detailed information on the bank data, see 4. Bank B's deposits in year t are defined as the savings accounts by non-bank customers in year t's balance sheet. We distinguish between loans granted by Bank B

to (i) its customers and to (ii) other banks. The variable loans to customers is defined as the sum of banks' outstanding claims against their (non-bank) customers as reported on the asset side of banks' balance sheets in year t. The variable loans to banks is defined similarly for banks' claims against other banks. In addition, we define loans from banks as the amount outstanding which bank B owes to other banks at the reporting of year t. When we analyze loans to banks, we further differentiate between short-term loans, which are payable on demand, and loans granted on a longer term , which are not payable on demand.[16]

We construct two ratios which describe banks' net lending to non-bank customers, Net lending, and banks' net interbank lending, Net lending^{IB}:

$$\text{Net lending}_{B,t} = \Delta log\left(\frac{\text{Loans to customers}_{B,t}}{\text{Deposits}_{B,t}}\right) \tag{5}$$

$$\text{Net lending}^{IB}_{B,t} = \Delta log\left(\frac{\text{Loans to banks}_{B,t}}{\text{Loans from banks}_{B,t}}\right) \tag{6}$$

In our analysis, we use two modified versions of Net lending$^{IB}_{B,t}$ for which we substitute loans to banks with short term and long term loans to banks.

4.2 Summary statistics

Table 1 reports summary statistics for the variables in our analysis. We split the overall standard deviation into a between and a within component. The between component reflects pure cross-sectional variation between the banks in our sample. In contrast, the within component measures only the variation over time. To account for outliers, all variables are winsorized at the 1% level at both tails of the distribution.

[16] Given out data, we cannot draw a more detailed distinction between short term and long term loans.

The first six variables that we report are the variables from which we construct the dependent variables, i.e bank-level amounts of deposits and loans. For all of these variables, the majority of the standard deviation stems from variation between different banks, which is not surprising, as our data set covers a large number of smaller banks, that operate on a local level only, and a few larger banks, which run a nation-wide branch network. The within standard deviation for the six variables is however substantial, i.e. it exceeds the arithmetic mean for 5 of the 6 variables and amounts for roughly a quarter to a third of the overall standard deviation of the variables.

The average bank in our sample reports savings deposits of 247.78 million Euros and a loan portfolio to non-bank customers of about 706 million Euros in their balance sheets. The Loan portfolio for loans obtained from and granted to other financial institutions amounts for 332.57 million Euros and 226.37 million Euros. The majority of the loans to other financial institutions are not payable on demand, i.e. classified as longer term loans.

The tourist exposure of the average bank is 1.23 millions, as measured by nights accommodation during the winter season. The average firm has a snow exposure of 191.7 snow days during the winter season. Both numbers vary substantially from one bank to another, as some banks operate only locally whereas others operate on a nationwide level. The within component of the standard deviation of tourist exposure (1.43 millions) and snow days (145.2) are also high. The variation can come from two sources: (i) variation over time in the number of nights accommodation and snow days in Austrian municipalities, and, (ii) changes in exposure introduced by changes in the banks branch network over time. Analyzing the raw data about nights accommodation (snow days), we find that the within variation accounts for 43% (68%) of the overall standard deviation, i.e. changes in banks' branch network do not further amplify the within variation in nights accommodation and snow days observed in the raw data.

5 Results

5.1 Banks' deposits and net lending to non-bank customers

In this subsection, we are interested in the effect of liquidity shocks caused by demand from tourists on bank level deposits and banks' lending policy to non-bank customers. Table 2 reports results for regressions of deposit growth on growth of the bank level exposure to tourists (in column 1 and 4) and snow (3). For all variables, i.e. deposits, number of tourists' overnight stays, and snow days, we use the first difference of the logarithm, i.e. the logarithmic growth rates in the regressions. In column 1, we regress deposit growth on the growth of tourists' overnight stays. We find a positive and significant relationship between deposit growth and the growth of bank level exposure to tourists. A 10 percentage point increase in the bank level exposure to tourists is associated with a 2.1 percentage points increase in deposits. In column 2, we report results for the reduced form regression of deposit growth on the growth of snow days. As in the OLS specification, the result is positive and significant. A 10 percentage point increase in bank level exposure to snow causes a 1 percentage point increase in deposits.

In column 3, we report results for the first stage regression of tourists overnight stays on snow. The results are comparable to those reported in Töglhofer et al. (2011). We find that the F-statistic for the significance of the excluded instruments is higher than the "rule of thumb" cutoff of 10 (see Staiger and Stock (1997)) and the most conservative cutoff of 16.38 suggested by Stock and Yogo (2005). Therefore, we conclude that this analysis does not suffer from weak identification. In column 4, we report results of the second stage regression of deposit growth on the growth of tourists' overnight stays. The estimate of the IV regression is also positive and significant. However, the magnitude of the IV coefficient is about 10 times higher when compared to the coefficient of the OLS regression, suggesting that the variable $Tourists$ is endogenous.[17] A one percentage point exogenous increase in the number of tourists' overnight stays causes a 2.5% growth in deposits.

Next, we analyze how banks translate the deposits into loans to non-bank customers. Table 3 reports results in which the dependent variable is the difference in loan and deposit growth rates. In column 1, we present results for an OLS regression. We do not find a systematic relation between the number of tourists' overnight stays and the difference in loan and deposit growth rates. Column 2 and 4 report results for the reduced form and the IV regressions in which we regress the difference in loan and deposit growth rates on snow. In both specifications, we find a negative and significant effect of snow on the difference in loan and deposit growth rates, i.e. banks increase their lending to customers (relative to their deposits from the customers) when deteriorating snow conditions lead to less tourists in ski resorts.[18] The effect is economically significant. When analyzing the IV coefficient in column 4, a one standard deviation decrease in tourist growth leads to an increase in the dependent variable by half a standard deviation. We interpret this finding as follows: Banks provide liquidity to their (non-bank) customers in the ski resorts when they need it the most, i.e. years in which there is few snow and there are only few tourists.

[17] In fact, we can reject exogeneity of tourists' overnight stays in an endogeneity test with a p-value of 1%.

[18] Again, we can reject exogeneity of tourists' overnight stays in an endogeneity test with a p-value of 1%.

5.2 Interbank borrowing and lending

In this subsection, we are interested in the effect of liquidity shocks caused by demand from tourists on the interbank borrowing and lending activities by banks. Table 4 reports results for similar regressions as in subsection 5.1 for net interbank lending. Our main dependent variable net interbank lending is defined as the difference between the growth rate of a bank's loans to other banks and that of the bank's loans from other banks. We do not find a significant relation between net interbank lending and the number of tourists in the OLS specification in column 1. In the reduced form specification in column 2, we find a positive and significant effect of snow on net interbank lending. We find the same effect in the IV specification in column 4: Banks perform less net interbank lending in bad winters with few tourists in ski resorts. A 10 percentage point decrease in banks' exposure to tourists causes a 8.6 percentage points decrease in net interbank lending. This pattern is consistent with our hypothesis that banks' net interbank lending is "crowded out" by their liquidity insurance to non-bank customers during bad winters.

We distinguish between short-term and long-term net lending to other banks. The results of a similar set of regressions as in the previous analysis are reported in tables 5 and 6. We find that it is the long-term and not the short-term net lending to other banks which is crowded out by net lending to non-bank customers during bad winters. This is consistent with the idea that banks use the interbank market to take on capital in order to provide liquidity insurance to their non-bank customers.

6 Cross-sectional variation in net lending

6.1 Local banks

In this subsection, we test whether there exist differences between local and non-local banks in the provision of liquidity insurance for non-bank customers and the lending activity on the interbank market. We exploit the "three-pillar" system of the Austrian banking market and define local banks as the group of savings banks and cooperative banks.[19] In contrast to the other banks, local banks operate on a strictly regional basis only. Not surprisingly, local banks are, on average, smaller than the remaining banks as measured by total assets and the number of branches. Following the idea of Stein (2002) and DeYoung, Hunter, and Udell (2004), because they are small, local banks might be particularly good in processing soft information about their small and informationally opaque customers in ski resorts. Therefore, we suspect mainly these banks to engage in relationship lending, and to be the main providers of liquidity insurance to non-bank customers.

Table 7 reports estimates of the second stage IV regressions in which we regress different dependent variables on bank level exposure to tourists. Exposure to tourists is instrumented by exposure to snow. The dependent variables are net lending to non-bank customers (column 1 and 2), net interbank lending (column 3 and 4), short-term net interbank lending (column 5 and 6), and long-term net interbank lending (column 7 and 8). The pattern of results in table 7 is consistent with this notion. In column 2 we find that only local banks provide its non-bank customers with liquidity insurance during bad years. Net interbank lending is negatively affected by the number of tourists only at local banks (see column 4 and 8 for long-term net interbank lending). This is consistent with the idea, that local banks borrow on the interbank

[19] For a discussion of the Austrian banking market, see 3.2

market in order to provide liquidity insurance to their non-bank customers. Next, we test for the significance in the difference between local and non-local banks. In table 8, we report results of an IV regression in which we instrument $\Delta log(Tourists)$ and $\Delta log(Tourists) \times$ Local bank with $\Delta log(Snow)$ and $\Delta log(Snow) \times$ Local bank. For net lending to non-bank customers, we find that the growth rate sensitivity to tourists is significantly lower at local banks. For (long-term) net interbank lending, the growth rate sensitivity to tourists is significantly higher at local banks.[20] We conclude that only for local banks, net interbank lending is crowded out by the provision of liquidity to non-bank customers during bad winters.

6.2 Bank capitalization

In this subsection, we test whether the capitalization of banks matters for net lending to non-bank customers and net interbank lending. The capitalization of banks is measured by the equity ratio of the bank lagged by one year. In table 9, we perform sample splits between bank-year with lagged equity ratios lower (L) and higher (H) than the median. We find that only the highly capitalized banks increase their net lending to their non-bank customers and decrease their net interbank lending (both short-term and long-term) in bad years. This pattern is consistent with the idea, that banks with sufficient capitalization borrow on the interbank market in order to provide liquidity insurance to their non-bank customers. In table 10, we test for a difference in β in equation 1 for banks with high and low capitalization. We do not find a significant interaction effect in any of the specifications. However, all the regressions suffer from weak identification as the F-test of excluded instruments in the first stage is below one. Therefore, it is difficult to interpret the results in table 10.

[20] The first stage F-statistic meets the criteria of Stock and Yogo (2005) for the desired maximal size of the Wald test of 0.2.

6.3 Snow risk

In this subsection, we test whether snow risk has an effect on the provision of liquidity insurance for non-bank customers and the lending activity in the interbank market. Snow risk is defined as the standard deviation of $Snow_{B,t}$ as defined in equation 4 across the entire sample period. The idea is that banks that face high levels of snow risk are hit more often by snow-induced liquidity shocks, which might limit their ability to provide insurance to their non-bank customers. In fact, in table 11, we find that only the banks that face relatively low levels of snow risks are the ones which provide liquidity insurance to their non-bank customers and perform less net interbank lending in bad years. However, we do not find the coefficients to be significantly different in table 12. [21]

6.4 Branch network diversification

In this subsection, we analyze the effect of the geographical diversification of a bank's branch network on the provision of liquidity insurance for non-bank customers and the lending activity on the interbank market. The idea is the following: The more geographically diversified the branch network of a bank is, the less the bank is hit by local snow-induced liquidity shocks. Therefore, a branch network diversification might foster the bank's ability to provide liquidity insurance to its non-bank customers. Branch network diversification is defined as the geographical expansion of the bank's branch network:

$$\text{Branch diversification}_{B,t} = \sum_{n \in B} \sqrt{(lat_{n,B,t} - \overline{lat_{B,T}})^2 + (lon_{n,B,t} - \overline{lon_{B,t}})^2} \tag{7}$$

[21] Again, all the regressions suffer from weak identification as the F-test of excluded instruments in the first stage is below one. Therefore, it is difficult to interpret the results in table 12.

where n indexes the branches of bank B. The hypothetical mid-branch location is given by $\overline{lat_{B,T}}$ and $\overline{lon_{B,T}}$ which are defined as the average latitude and longitude of all of bank B's branches in year t.

We define a bank's branch network to be highly diversified if the geographical expansion of its branch network is larger than that of the median bank.

The results in table 13 suggest that banks with highly diversified branch networks (as reported in columns labeled H) are the banks which provide liquidity insurance to its non-bank customers during bad years. The same banks engage in less net interbank lending in these years. Again, we do not find the coefficients to be significantly different in table 14.[22]

7 Conclusion

In this paper, we demonstrate that banks provide liquidity insurance to their non-bank customers when hit by an exogenous liquidity shock. In contrast, banks net interbank borrowing is negatively affected by the liquidity shocks, i.e. banks borrow more than they lend in bad years. In other words, lending to other banks is "crowded out" by banks' provision of liquidity insurance to their non-bank customers. We find that this is the case for long-term but not for short-term net interbank lending.

In addition, we document cross-sectional variation in this finding. The insurance provision to non-bank customers in bad years comes from local banks, banks for which capitalization is sufficiently high, banks facing relatively low snow risk, and banks whose branch network is sufficiently diversified geographically. The same banks decrease their net interbank lending, or, in other words increase their net interbank borrowing in bad years.

[22] However, all the regressions suffer from weak identification as the F-test of excluded instruments in the first stage is below one. Therefore, it is difficult to interpret the results in table 14.

By focusing on weather-induced risk, the papers in this thesis add to the literature on economic adaptation to climate change. Due to climate change, negative snow induced shocks are expected to happen more frequently in the future. We show that banks are an important source of liquidity, and, therefore, an important source of stability for small firms in the tourism industry. This finding generalizes to other small firms in weather dependent industries.

References

Barrieu, P. and O. Scaillet (2010). *Weather Derivatives.* American Cancer Society.

Baumgartner, S., T. Schober, A. Stomper, and R. Winter-Ebmer (2020). Weather risk and employment: Banking on snow. Working Paper.

Bülbül, D., R. H. Schmidt, and U. Schüwer (2014). Savings banks and cooperative banks in Europe. *Bezpieczny Bank 2(55)*, 38–49.

DeYoung, R., W. Hunter, and G. Udell (2004). The past, present, and probable future for community banks. *Journal of Financial Services Research 25*(2), 85–133.

Doerflinger, C., A. Doerflinger, K. Gavac, and B. Vogl (2013). *Familienunternehmen in Oesterreich.* KMU Forschung Austria.

DSGV (2012). Inside the savings banks finance group.

ECB (2017). Report on financial structures.

Holmstrom, B. and J. Tirole (1998). Private and public supply of liquidity. *Journal of Political Economy 106*(1), 1–40.

Iyer, R., S. Lopes, J.-L. Peydro, and A. Schoar (2014, 01). Interbank liquidity crunch and the firm credit crunch: Evidence from the 2007-2009 crisis. *Review of Financial Studies 27*, 347–372.

Kashyap, A., R. Rajan, and J. Stein (2002, 02). Banks as liquidity providers: An explanation for the coexistence of lending and deposit-taking. *Journal of Finance 57*, 33–73.

Khwaja, A. I. and A. Mian (2008, September). Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market. *American Economic Review 98*(4), 1413–1442.

Paravasini, D. (2008). Local bank financial constraints and firm access to external finance. *The Journal of Finance 63*(5), 2161–2193.

Pichler, P., A. Stomper, and C. Zulehner (2008, July). Why Leverage Affects Pricing. *Review of Financial Studies 21*(4), 1733–1765.

Salzburger Nachrichten (2015). Beschneiungsanlagen. https://www.sn.at/wiki/Beschneiungsanlage. Accessed: 2020-05-10.

Schnabl, P. (2012). The international transmission of bank liquidity shocks: Evidence from an emerging market. *The Journal of Finance 67*(3), 897–932.

Staiger, D. and J. H. Stock (1997, May). Instrumental Variables Regression with Weak Instruments. *Econometrica 65*(3), 557–586.

Statistics Austria (2018). *Tourismus-Satellitenkonto.* https://www.statistik.at/web_de/statistiken/wirtschaft/tourismus/tourismus-satellitenkonto/wertschoepfung/index.html, (accessed May 28, 2020).

Stein, J. C. (2002). Information production and capital allocation: Decentralized versus hierarchical firms. *The Journal of Finance 57*(5), 1891–1921.

Stock, J. and M. Yogo (2005). *Testing for Weak Instruments in Linear IV Regression*, pp. 80–108. New York: Cambridge University Press.

Tirol Tourism Research (2018). *Wirtschaftliche Bedeutung des Tourismus.* https://www.ttr.tirol/statistik/wirtschaftliche-bedeutung-des-tourismus, (accessed May 28, 2020).

Töglhofer, C., F. Eigner, and F. Prettenthaler (2011). Impacts of snow conditions on tourism demand in Austrian ski areas. *Climate Research 46*(1), 1–14.

Figures and Tables

Figure 1: Branch network over time

This figure depicts the number of bank branches (solid line) and banks (dashed) over the years 1998) to 2012. The solid (dashed) line refers to the left (right) vertical axis.

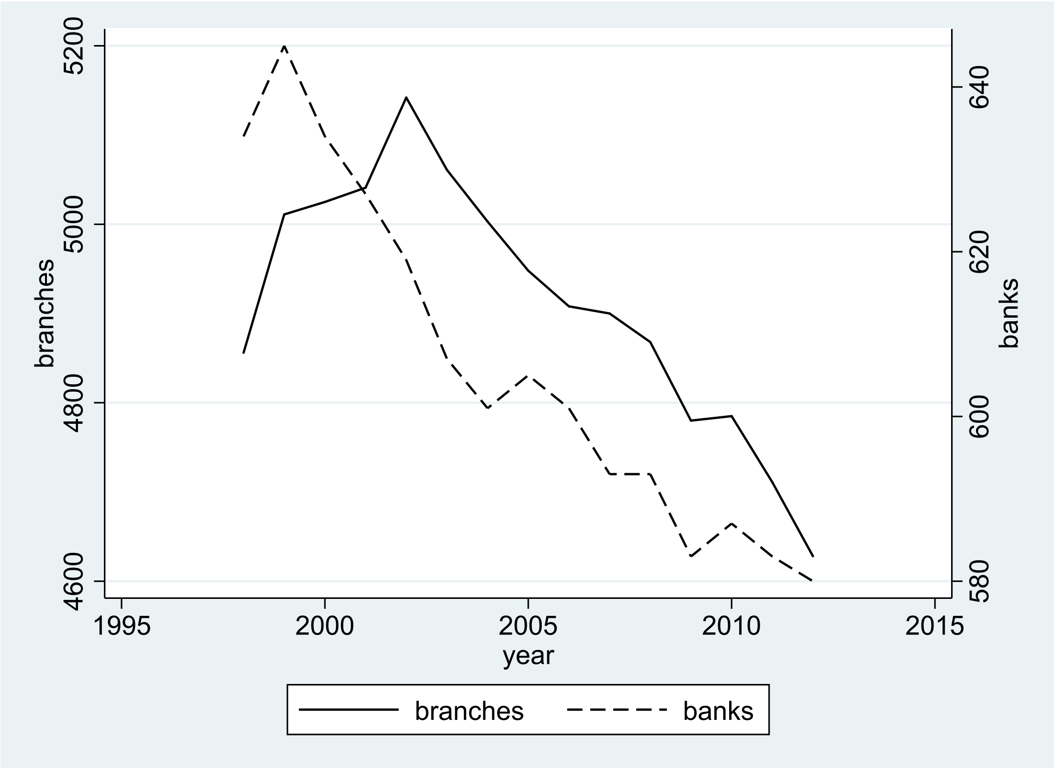

Table 1: Summary statistics

This table reports the mean, the standard deviation, the minimum, the maximum and the number of observations for the variables of interest. The data set has a bank-year panel structure. We split the overall standard deviation into a between and a within component. The between component reflects pure cross-sectional variation between the hotels in our sample. We winsorize 1% on both ends of the distribution for all continuous variables.

Variable	Category	Mean	SD	Min	Max	Obs
Deposits (mio.)	overall	247.78	807.97	0	7043.48	9802
	between		736.81			653
	within		214.09			15
Loans to customers (mio.)	overall	706.02	3290.95	0	27654.15	9802
	between		3106.66			653
	within		801.57			15
Loans to banks (mio.)	overall	226.37	1047.66	0	8833.77	9802
	between		986.79			653
	within		321.18			15
Loans from banks (mio.)	overall	332.57	1882.75	0	16127.17	9802
	between		1782.77			653
	within		522.96			15
Short term loans to banks (mio.)	overall	51.41	182.14	0	1581.57	9802
	between		165.61			653
	within		71.16			15
Long term loans to banks (mio.)	overall	170.61	861.91	0	7281.33	9802
	between		805.68			653
	within		284			15
Tourists (in thousands)	overall	1231.78	4650.05	0	37209.78	6147
	between		4198.36			586
	within		1426.18			10.49
Snow	overall	191.73	286.76	0	1860.62	7336
	between		234.55			653
	within		145.24			11.23

Table 2: Effect of liquidity shocks on bank deposits.

This table reports estimates for regressions of bank level deposit growth on the growth of banks' exposure to tourists and snow. We report OLS estimates for a regression of deposit growth on tourist growth in column 1. In column 2, we present results for a reduced form specification, where we regress deposit growth on snow growth. Column 3 and 4 report the first stage results (column 3) and second stage results (column 4) of an IV regression of deposit growth on growth in tourists, where we instrument bank level exposure to tourists with bank level exposure to snow. All regressions include bank and year fixed effects to control for time-invariant heterogeneity on the bank level and general macroeconomic fluctuation over the years. At the bottom of the table, we report the Cragg-Donald Wald F-statistic for first stage regression of IV estimation, and the p-value of the standard "difference-in-Sargan" test (provided by STATA's ivreg2 command) for endogeneity of $\Delta log(Tourists)$. We winsorize 1% on both ends of the distribution for all variables. Standard errors are clustered at the bank level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	$\Delta log(Deposits)$		$\Delta log(Tourists)$	$\Delta log(Deposits)$
$\Delta log(Tourists)$	0.212^{**}			2.510^{***}
	(0.0837)			(0.957)
$\Delta log(Snow)$		0.0951^{***}	0.0292^{***}	
		(0.0266)	(0.00655)	
N	5997	7094	5392	5392
AdjR2	0.01	0.02		
Bank FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
1st stage F-Test			19.89	
Endogeneity test (p-value)				0.01

Table 3: Liquidity shocks and net lending to non-bank customers.

This table reports estimates for regressions describing the relation between a bank's lending policy to non-bank customers and their exposure to tourists and snow. The dependent variable in columns 1, 2, and 3 is the difference in the logarithmic growth rates of banks' loans to non-bank customers and their deposits. We report OLS estimates for a regression of the difference between loan and deposit growth on tourist growth in column 1. In column 2, we present results for a reduced form specification, where we regress the difference between loan and deposit growth on snow growth. Column 3 and 4 report the first stage results (column 3) and second stage results (column 4) of an IV regression of the difference between loan and deposit growth on growth in tourists, where we instrument bank level exposure to tourists with bank level exposure to snow. All regressions include bank and year fixed effects to control for time-invariant heterogeneity on the bank level and general macroeconomic fluctuation over the years. At the bottom of the table, we report the Cragg-Donald Wald F-statistic for first stage regression of IV estimation, and the p-value of the standard "difference-in-Sargan" test (provided by STATA's ivreg2 command) for endogeneity of $\Delta log(Tourists)$. We winsorize 1% on both ends of the distribution for all variables. Standard errors are clustered at the bank level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	$\Delta log(\frac{\text{Loans to customers}}{\text{Deposits}})$		$\Delta log(Tourists)$	$\Delta log(\frac{\text{Loans to customers}}{\text{Deposits}})$
$\Delta log(Tourists)$	0.000961			-0.0714**
	(0.00205)			(0.0332)
$\Delta log(Snow)$		-0.00193***	0.0292***	
		(0.000671)	(0.00655)	
N	5997	7094	5392	5392
AdjR2	0.09	0.09		
Bank FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
1st stage F-Test			19.89	
Endogeneity test (p-value)				0.01

Table 4: Liquidity shocks and net interbank lending.

This table reports estimates for regressions describing the relation between a bank's net interbank lending and their exposure to tourists and snow. The dependent variable in columns 1, 2, and 3 is the difference in the logarithmic growth rates between loans granted to and taken from other financial institutions. We report OLS estimates for a regression of net interbank lending on tourist growth in column 1. In column 2, we present results for a reduced form specification, where we regress the difference between loan and deposit growth on snow growth. Column 3 and 4 report the first stage results (column 3) and second stage results (column 4) of an IV regression of net interbank lending on tourists, where we instrument bank level exposure to tourists with bank level exposure to snow. All regressions include bank and year fixed effects to control for time-invariant heterogeneity on the bank level and general macroeconomic fluctuation over the years. At the bottom of the table, we report the Cragg-Donald Wald F-statistic for first stage regression of IV estimation, and the p-value of the standard "difference-in-Sargan" test (provided by STATA's ivreg2 command) for endogeneity of $\Delta log(Tourists)$. We winsorize 1% on both ends of the distribution for all variables. Standard errors are clustered at the bank level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	$\Delta log(\frac{\text{Loans to banks}}{\text{Loans from banks}})$		$\Delta log(Tourists)$	$\Delta log(\frac{\text{Loans to banks}}{\text{Loans from banks}})$
$\Delta log(Tourists)$	0.0210			0.855**
	(0.0260)			(0.409)
$\Delta log(Snow)$		0.0186**	0.0292***	
		(0.00945)	(0.00655)	
N	5997	7094	5392	5392
AdjR2	0.02	0.03		
Bank FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
1st stage F-Test			19.89	
Endogeneity test (p-value)				0.02

Table 5: Liquidity shocks and short-term net interbank lending.

This table reports estimates for regressions describing the relation between a bank's short-term net interbank lending and their exposure to tourists and snow. The dependent variable in columns 1, 2, and 3 is the difference in the logarithmic growth rates between short-term loans granted to other financial institutions and loans (of all maturities) taken from other financial institutions. We report OLS estimates for a regression of net interbank lending on tourist growth in column 1. In column 2, we present results for a reduced form specification, where we regress the difference between loan and deposit growth on snow growth. Column 3 and 4 report the first stage results (column 3) and second stage results (column 4) of an IV regression of net interbank lending on tourists, where we instrument bank level exposure to tourists with bank level exposure to snow. All regressions include bank and year fixed effects to control for time-invariant heterogeneity on the bank level and general macroeconomic fluctuation over the years. At the bottom of the table, we report the Cragg-Donald Wald F-statistic for first stage regression of IV estimation, and the p-value of the standard "difference-in-Sargan" test (provided by STATA's ivreg2 command) for endogeneity of $\Delta log(Tourists)$. We winsorize 1% on both ends of the distribution for all variables. Standard errors are clustered at the bank level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	$\Delta log(\frac{\text{s.t. loans to banks}}{\text{Loans from banks}})$		$\Delta log(Tourists)$	$\Delta log(\frac{\text{s.t. loans to banks}}{\text{Loans from banks}})$
$\Delta log(Tourists)$	-0.000454			0.460
	(0.0265)			(0.370)
$\Delta log(Snow)$		0.00567	0.0292***	
		(0.00918)	(0.00655)	
N	5997	7094	5392	5392
AdjR2	0.02	0.02		
Bank FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
1st stage F-Test			19.89	
Endogeneity test (p-value)				0.17

Table 6: Liquidity shocks and long-term net interbank lending.

This table reports estimates for regressions describing the relation between a bank's long-term net interbank lending and their exposure to tourists and snow. The dependent variable in columns 1, 2, and 3 is the difference in the logarithmic growth rates between long-term loans granted to other financial institutions and loans (of all maturities) taken from other financial institutions. We report OLS estimates for a regression of net interbank lending on tourist growth in column 1. In column 2, we present results for a reduced form specification, where we regress the difference between loan and deposit growth on snow growth. Column 3 and 4 report the first stage results (column 3) and second stage results (column 4) of an IV regression of net interbank lending on tourists, where we instrument bank level exposure to tourists with bank level exposure to snow. All regressions include bank and year fixed effects to control for time-invariant heterogeneity on the bank level and general macroeconomic fluctuation over the years. At the bottom of the table, we report the Cragg-Donald Wald F-statistic for first stage regression of IV estimation, and the p-value of the standard "difference-in-Sargan" test (provided by STATA's ivreg2 command) for endogeneity of $\Delta log(Tourists)$. We winsorize 1% on both ends of the distribution for all variables. Standard errors are clustered at the bank level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	$\Delta log(\frac{\text{l.t. loans to banks}}{\text{Loans from banks}})$		$\Delta log(Tourists)$	$\Delta log(\frac{\text{l.t. loans to banks}}{\text{Loans from banks}})$
$\Delta log(Tourists)$	0.00553			0.863**
	(0.0233)			(0.390)
$\Delta log(Snow)$		0.0192**	0.0292***	
		(0.00895)	(0.00655)	
N	5997	7094	5392	5392
AdjR2	0.02	0.02		
Bank FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
1st stage F-Test			19.89	
Endogeneity test (p-value)				0.01

Table 7: Sample splits: Local and non-local banks.

This table reports results comparable to those in column 4 of the table 3. We report estimates of the second stage IV regressions in which we regress different dependent variables on bank level exposure to tourists, instrumented by the exposure to snow. The dependent variables are net lending to non-bank customers (column 1 and 2), net interbank lending (column 3 and 4), short-term net interbank lending (column 5 and 6), and long-term net interbank lending (column 7 and 8). Columns labeled as "LB" present results for the subset of local banks, i.e. banks which belong to the group of savings banks and cooperative banks. Columns labeled as "¬ LB" present results for all other banks. All regressions include bank and year fixed effects to control for time-invariant heterogeneity on the bank level and general macroeconomic fluctuation over the years. At the bottom of the table, we report the p-value of the standard "difference-in-Sargan" test (provided by STATA's ivreg2 command) for endogeneity of $\Delta log(Tourists)$. We winsorize 1% on both ends of the distribution for all variables. Standard errors are clustered at the bank level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	$\Delta log(\frac{\text{Loans to customers}}{\text{Deposits}})$		$\Delta log(\frac{\text{Loans to banks}}{\text{Loans from banks}})$		$\Delta log(\frac{\text{s.t. loans to banks}}{\text{Loans from banks}})$		$\Delta log(\frac{\text{l.t. loans to banks}}{\text{Loans from banks}})$	
	¬ LB	LB	¬ LB	LB	¬ LB	LB	¬ LB	LB
$\Delta log(Tourists)$	0.0410	-0.141**	0.439	1.097*	-0.203	0.668	0.578	1.191*
	(0.0579)	(0.0593)	(0.509)	(0.659)	(0.481)	(0.579)	(0.454)	(0.653)
N	542	4849	542	4849	542	4849	542	4849
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
1st stage F-Test	10.71	9.77	10.71	9.77	10.71	9.77	10.71	9.77
Endogeneity test (p-value)	0.70	0.00	0.58	0.04	0.74	0.19	0.32	0.02

Table 8: Differences between local and non-local banks.

This table reports results comparable to those in column 4 of the table 3. We report estimates of the second stage IV regressions in which we regress different dependent variables on bank level exposure to tourists, instrumented by the exposure to snow. We include a second variable: The interaction between bank level exposure to tourists and a dummy variable for local banks and use a similar interaction of the local bank dummy and banks' exposure to snow as a second instrument. The dependent variables are net lending to non-bank customers (column 1), net interbank lending (column 2), short-term net interbank lending (column 3), and long-term net interbank lending (column 4). All regressions include bank and year fixed effects to control for time-invariant heterogeneity on the bank level and general macroeconomic fluctuation over the years. At the bottom of the table, we report the p-value of the standard "difference-in-Sargan" test (provided by STATA's ivreg2 command) for endogeneity of $\Delta log(Tourists)$. We winsorize 1% on both ends of the distribution for all variables. Standard errors are clustered at the bank level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	$\Delta log(\frac{\text{Loans to customers}}{\text{Deposits}})$	$\Delta log(\frac{\text{Loans to banks}}{\text{Loans from banks}})$	$\Delta log(\frac{\text{s.t. loans to banks}}{\text{Loans from banks}})$	$\Delta log(\frac{\text{l.t. loans to banks}}{\text{Loans from banks}})$
$\Delta log(Tourists)$	0.0445	-0.428	-0.247	-0.424
	(0.0379)	(0.417)	(0.370)	(0.389)
$\Delta log(Tourists) \times$ Local bank	-0.186**	2.072*	1.141	2.080**
	(0.0882)	(1.107)	(0.909)	(1.048)
N	5392	5392	5392	5392
Bank FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Cragg-Donald Wald F-Test	3.98	3.98	3.98	3.98
Endogeneity test (p-value)	0.01	0.03	0.31	0.02

Table 9: Sample splits: High and low bank capitalization.

This table reports results comparable to those in column 4 of the table 3. We report estimates of the second stage IV regressions in which we regress different dependent variables on bank level exposure to tourists, instrumented by the exposure to snow. The dependent variables are net lending to non-bank customers (column 1 and 2), net interbank lending (column 3 and 4), short-term net interbank lending (column 5 and 6), and long-term net interbank lending (column 7 and 8). We split the sample between bank-years in which the first lag of bank capitalization was high and low. Columns labeled as “L” (“H”) present results for the subset of bank-years for which the lagged equity ratios were lower (higher) than the median. All regressions include bank and year fixed effects to control for time-invariant heterogeneity on the bank level and general macroeconomic fluctuation over the years. At the bottom of the table, we report the p-value of the standard “difference-in-Sargan” test (provided by STATA’s ivreg2 command) for endogeneity of $\Delta log(Tourists)$. We winsorize 1% on both ends of the distribution for all variables. Standard errors are clustered at the bank level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	$\Delta log(\frac{\text{Loans to customers}}{\text{Deposits}})$		$\Delta log(\frac{\text{Loans to banks}}{\text{Loans from banks}})$		$\Delta log(\frac{\text{s.t. loans to banks}}{\text{Loans from banks}})$		$\Delta log(\frac{\text{l.t. loans to banks}}{\text{Loans from banks}})$	
	L	H	L	H	L	H	L	H
$\Delta log(Tourists)$	-0.0697	-0.0849*	-0.102	1.573**	-0.304	1.275*	0.0206	1.282**
	(0.0668)	(0.0465)	(0.609)	(0.720)	(0.589)	(0.664)	(0.621)	(0.614)
N	2359	2366	2359	2366	2359	2366	2359	2366
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
1st stage F-Test	4.16	13.43	4.16	13.43	4.16	13.43	4.16	13.43
Endogeneity test (p-value)	0.25	0.02	0.90	0.01	0.69	0.03	0.94	0.02

Table 10: Differences between banks with high and low capitalization.

This table reports results comparable to those in column 4 of the table 3. We report estimates of the second stage IV regressions in which we regress different dependent variables on bank level exposure to tourists, instrumented by the exposure to snow. We include a second variable: The interaction between bank level exposure to tourists and the first lag of banks' equity ratio and use a similar interaction of and the first lag of banks' equity ratio and banks' exposure to snow as a second instrument. The dependent variables are net lending to non-bank customers (column 1), net interbank lending (column 2), short-term net interbank lending (column 3), and long-term net interbank lending (column 4). All regressions include bank and year fixed effects to control for time-invariant heterogeneity on the bank level and general macroeconomic fluctuation over the years. At the bottom of the table, we report the p-value of the standard "difference-in-Sargan" test (provided by STATA's ivreg2 command) for endogeneity of $\Delta log(Tourists)$. We winsorize 1% on both ends of the distribution for all variables. Standard errors are clustered at the bank level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	$\Delta log(\frac{\text{Loans to customers}}{\text{Deposits}})$	$\Delta log(\frac{\text{Loans to banks}}{\text{Loans from banks}})$	$\Delta log(\frac{\text{s.t. loans to banks}}{\text{Loans from banks}})$	$\Delta log(\frac{\text{l.t. loans to banks}}{\text{Loans from banks}})$
$\Delta log(Tourists)$	0.0868	-1.454	-2.100	-0.404
	(0.146)	(2.276)	(2.532)	(1.634)
$\Delta log(Tourists) \times Lag$(High Equity Ratio)	-0.259	3.872	4.321	2.057
	(0.248)	(3.716)	(3.987)	(2.731)
Lag(High Equity Ratio)	0.00158	-0.0334	-0.0247	-0.0374
	(0.00323)	(0.0367)	(0.0400)	(0.0282)
N	4781	4781	4781	4781
Bank FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Cragg-Donald Wald F-Test	0.66	0.66	0.66	0.66
Endogeneity test (p-value)	0.01	0.04	0.09	0.08

Table 11: Sample splits: Snow Risk

This table reports results comparable to those in column 4 of the table 3. We report estimates of the second stage IV regressions in which we regress different dependent variables on bank level exposure to tourists, instrumented by the exposure to snow. The dependent variables are net lending to non-bank customers (column 1 and 2), net interbank lending (column 3 and 4), short-term net interbank lending (column 5 and 6), and long-term net interbank lending (column 7 and 8). We split the sample in terms of banks' snow risk. Snow risk is defined as the standard deviation of *Snow* across all years of the sample period. Columns labeled as "L" ("H") present results for the subset of banks whose snow risk is lower (higher) than that of the median bank. All regressions include bank and year fixed effects to control for time-invariant heterogeneity on the bank level and general macroeconomic fluctuation over the years. At the bottom of the table, we report the p-value of the standard "difference-in-Sargan" test (provided by STATA's ivreg2 command) for endogeneity of $\Delta log(Tourists)$. We winsorize 1% on both ends of the distribution for all variables. Standard errors are clustered at the bank level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	$\Delta log(\frac{\text{Loans to customers}}{\text{Deposits}})$		$\Delta log(\frac{\text{Loans to banks}}{\text{Loans from banks}})$		$\Delta log(\frac{\text{s.t. loans to banks}}{\text{Loans from banks}})$		$\Delta log(\frac{\text{l.t. loans to banks}}{\text{Loans from banks}})$	
	L	H	L	H	L	H	L	H
$\Delta log(Tourists)$	-0.0969*	-0.0511	1.400*	0.512	0.615	0.428	1.539*	0.394
	(0.0572)	(0.0394)	(0.787)	(0.411)	(0.704)	(0.378)	(0.806)	(0.351)
N	2678	2714	2678	2714	2678	2714	2678	2714
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
1st stage F-Test	8.23	11.55	8.23	11.55	8.23	11.55	8.23	11.55
Endogeneity test (p-value)	0.04	0.11	0.05	0.16	0.32	0.20	0.03	0.23

Table 12: Differences between banks with high and low snow risk.

This table reports results comparable to those in column 4 of the table 3. We report estimates of the second stage IV regressions in which we regress different dependent variables on bank level exposure to tourists, instrumented by the exposure to snow. We include a second variable: The interaction between bank level exposure to tourists and the dummy variable high snow risk. Snow risk is defined as the standard deviation of *Snow* across all years of the sample period. High snow risk equals one if the snow risk is higher than that of the median bank, and zero else. The dependent variables are net lending to non-bank customers (column 1), net interbank lending (column 2), short-term net interbank lending (column 3), and long-term net interbank lending (column 4). All regressions include bank and year fixed effects to control for time-invariant heterogeneity on the bank level and general macroeconomic fluctuation over the years. At the bottom of the table, we report the p-value of the standard "difference-in-Sargan" test (provided by STATA's ivreg2 command) for endogeneity of $\Delta log(Tourists)$. We winsorize 1% on both ends of the distribution for all variables. Standard errors are clustered at the bank level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	$\Delta log(\frac{\text{Loans to customers}}{\text{Deposits}})$	$\Delta log(\frac{\text{Loans to banks}}{\text{Loans from banks}})$	$\Delta log(\frac{\text{s.t. loans to banks}}{\text{Loans from banks}})$	$\Delta log(\frac{\text{l.t. loans to banks}}{\text{Loans from banks}})$
$\Delta log(Tourists)$	-0.316	2.354	-0.260	2.963
	(0.355)	(2.796)	(1.936)	(3.281)
$\Delta log(Tourists) \times$ High Snow Risk	0.438	-2.685	1.289	-3.761
	(0.562)	(4.462)	(3.243)	(5.209)
N	5392	5392	5392	5392
Bank FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Cragg-Donald Wald F-Test	0.46	0.46	0.46	0.46
Endogeneity test (p-value)	0.02	0.07	0.21	0.05

Table 13: Sample splits: Branch network diversification

This table reports results comparable to those in column 4 of the table 3. We report estimates of the second stage IV regressions in which we regress different dependent variables on bank level exposure to tourists, instrumented by the exposure to snow. The dependent variables are net lending to non-bank customers (column 1 and 2), net interbank lending (column 3 and 4), short-term net interbank lending (column 5 and 6), and long-term net interbank lending (column 7 and 8). We split the sample in terms of banks' branch network diversification (as defined in equation 7. Columns labeled as "L" ("H") present results for the subset of banks whose branch network diversification is lower (higher) than that of the median bank. All regressions include bank and year fixed effects to control for time-invariant heterogeneity on the bank level and general macroeconomic fluctuation over the years. At the bottom of the table, we report the p-value of the standard "difference-in-Sargan" test (provided by STATA's ivreg2 command) for endogeneity of $\Delta log(Tourists)$. We winsorize 1% on both ends of the distribution for all variables. Standard errors are clustered at the bank level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	$\Delta log(\frac{\text{Loans to customers}}{\text{Deposits}})$		$\Delta log(\frac{\text{Loans to banks}}{\text{Loans from banks}})$		$\Delta log(\frac{\text{s.t. loans to banks}}{\text{Loans from banks}})$		$\Delta log(\frac{\text{l.t. loans to banks}}{\text{Loans from banks}})$	
	L	H	L	H	L	H	L	H
$\Delta log(Tourists)$	-0.221	-0.0681*	3.062	0.622**	0.944	0.269	3.932	0.595**
	(0.308)	(0.0353)	(4.542)	(0.301)	(3.009)	(0.262)	(5.160)	(0.301)
N	2681	2711	2681	2711	2681	2711	2681	2711
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
1st stage F-Test	0.66	18.17	0.66	18.17	0.66	18.17	0.66	18.17
Endogeneity test (p-value)	0.16	0.02	0.30	0.03	0.72	0.28	0.15	0.03

Table 14: Differences between banks with high and low branch network diversification.

This table reports results comparable to those in column 4 of the table 3. We report estimates of the second stage IV regressions in which we regress different dependent variables on bank level exposure to tourists, instrumented by the exposure to snow. We include a second variable: The interaction between bank level exposure to tourists and the dummy variable high branch network diversification. Banks' branch network diversification is defined in equation 7. We define banks' branch network to be highly diversified if the branch network diversification is higher (higher) than that of the median bank. The dependent variables are net lending to non-bank customers (column 1), net interbank lending (column 2), short-term net interbank lending (column 3), and long-term net interbank lending (column 4). All regressions include bank and year fixed effects to control for time-invariant heterogeneity on the bank level and general macroeconomic fluctuation over the years. At the bottom of the table, we report the p-value of the standard "difference-in-Sargan" test (provided by STATA's ivreg2 command) for endogeneity of $\Delta log(Tourists)$. We winsorize 1% on both ends of the distribution for all variables. Standard errors are clustered at the bank level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	$\Delta log(\frac{\text{Loans to customers}}{\text{Deposits}})$	$\Delta log(\frac{\text{Loans to banks}}{\text{Loans from banks}})$	$\Delta log(\frac{\text{s.t. loans to banks}}{\text{Loans from banks}})$	$\Delta log(\frac{\text{l.t. loans to banks}}{\text{Loans from banks}})$
$\Delta log(Tourists)$	0.116	-0.938	0.768	-1.558
	(0.117)	(1.656)	(1.412)	(1.836)
$\Delta log(Tourists)$ × Branch Diversification	-0.224	2.138	-0.368	2.888
	(0.159)	(2.320)	(1.992)	(2.564)
N	5392	5392	5392	5392
Bank FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Cragg-Donald Wald F-Test	1.23	1.23	1.23	1.23
Endogeneity test (p-value)	0.02	0.05	0.06	0.05

Risk and Employment: Banking on Snow

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June 2020

Abstract

How does small-firm employment respond to labor productivity risk? We show that this depends on the equity capital of local banks. Our analysis is based on a truly quasi-experimental setting. We use highly granular data about a sample of small firms employing workers whose productivity depends on the weather. The data allow us to cleanly identify the causal effect of labor productivity risk on the firms' employment. We find that an increase in the risk of transitory productivity shocks reduces firms' willingness to commit to employing workers. This effect is stronger if local banks have less equity capital. It appears that a lack of bank equity reduces firms' capacity to take labor productivity risk. Our evidence also highlights that bank capitalization matters for economic adaptation to climate change by reducing the effects of increased weather variability on small-firm employment.

"making finance flows [...] consistent with climate-resilient development."

from Article 2 of the Paris Agreement, UNFCCC (2016)

1 Introduction

It is widely believed that the depth of the Great Recession was amplified by a combination of risk with financial frictions.[1] This toxic combination has since been the subject of a growing literature. The literature analyzes how the financial system fails firms and their owners when they need it to manage an increase in risk, and how this failure affects the firms' workers and the wider economy. In a recent contribution Arellano, Bai, and Kehoe (2019) show that they can match the contraction in employment and output observed during the Great Recession using a model in which firms take risk when they hire workers, promising them pay before they generate uncertain revenues. In the model, a contraction is triggered by an increase in the volatility of worker productivity. This occurs against the backdrop of capital market imperfections and agency problems that increase the cost of holding cash as a way to insure against liquidity shocks. A related model with different financial frictions appears in Quadrini (2017).[2]

This paper analyzes effects of exogenous changes in labor productivity risk induced by weather risk, based on a sample of firms exposed to climate change.[3] The firms are hotels in Austrian ski resorts. The productivity of their workers depends on skiers' demand for accommodation and, hence, on the snow conditions. We analyze how the firms' employment responds to variation in snow risk across years and across the weeks of the skiing season. The variation across years is particularly pronounced in ski resorts at high levels of altitude,

[1] For example, see Stock and Watson (2012).
[2] See the next section for a discussion of the related literature.
[3] The effect of the weather on labor productivity is the subject of a literature surveyed by Dell, Jones, and Olken (2014).

where snow risk increased due to a warming climate.[4] Our analysis identifies employment effects of variation in snow risk as a cause of labor productivity risk that the firms in our sample were clearly aware of.[5]

Our sample also allows us to distinguish between two types of labor productivity risk, i.e., those caused by the risks of a transitory and permanent lack of snow. At the start of the skiing season, snow risk is a risk of transitory negative shocks, but it is a risk of permanent negative shocks at the season's end. Our analysis starts with tests concerning the effects of the different snow shocks on the firms' employment. We document that, while the firms fire workers in response to permanent negative snow shocks, their employment is quasi-fixed with respect to transitory shocks.[6] We then focus on the risk of the latter shocks and find that, even though the shocks have no direct effects, the firms' employment responds to changes in the risk of these shocks. In essence, the firms behave like those in the models of Quadrini (2017) and Arellano et al. (2019): At times of higher risk, they employ fewer workers because they anticipate that, due to a transitory lack of snow, the workers might not be able to "earn their pay".

While we cannot directly observe the reasons for the risk aversion the firms exhibit in their hiring decisions, we test for effects of variables describing the risk-taking capacity of local banks. In this respect, our research strategy is motivated by the analysis of Holmström and Tirole (1998). They show that firms benefit from insurance against liquidity shocks provided by financial intermediaries, but agency problems can limit the optimal extent of this insurance provision, hence reducing firm size.[7] For the firms in our sample, the relevant

[4] See Section 5.2.1.

[5] This allows us to relate our results to predictions of models in which firms respond to changes in labor productivity risk.

[6] This is consistent with prior findings of Guiso, Pistaferri, and Schivardi (2005) and follow-up papers. In contrast to the prior literature, we can avoid identifying assumptions required to identify permanent and transitory shocks.

[7] Also, investments with a positive net present value may not be feasible without bank liquidity creation (Donaldson, Piacentino and Thakor (2018)).

liquidity shocks are the losses caused by a transitory lack of snow in ski resorts. As discussed above, the risk of these losses reduces firm size measured in terms of employment. We next test whether the strength of this effect depends on proxies for the risk-taking capacity of local banks.[8] The main result is evidence for an effect of bank capitalization that was not previously documented. We find that a lack of bank equity strengthens the negative effect of labor productivity risk on the firms' employment. As discussed below, this evidence results from instrumental-variables estimates that allow us to specifically talk about labor productivity risk (rather than snow risk). Our evidence is consistent with the idea that banks' capital structures affect their capacity to provide firms with liquidity insurance.[9] This insurance appears to be important for firms whose employment is quasi-fixed with respect to (transitory) shocks to worker productivity.

By focusing on weather-induced risk, we add to the literature on economic adaptation to climate change. Our evidence suggests that adverse effects of weather risk on employment are more pronounced if banks lack equity capital. Given that weather risk is a risk of rather verifiable shocks, it should in principle be well-suited for risk-sharing between small firms and their banks. By pooling the risks of many small firms in their vicinity, banks can realize economies of scale in risk management. Our results suggest that banks' performance as risk-sharing partners of small firms depends on their equity capital. As a consequence, banks' capital structure policies and their risk management

[8] See Elsas and Krahnen (1998) for evidence that firms in Germany rely on their housebanks for liquidity insurance. We use data about Austrian firms. The banking sectors of Austria and Germany operate in similar ways. For further information, see Section 3.2.

[9] In the framework of Holmström and Tirole (1998), the effect of equity capital can be formalized of as an effect of a (shadow) cost of liquidity insurance. For example, consider the simple model in Section 5.3.1. of Tirole (2006), where financial intermediaries incur no cost when they inject liquidity into a firm. Adding a cost parameter κ to the model reveals that this parameter modulates the effect of liquidity risk on the optimal firm size, $I = A/(1 - \rho_0 + (1 + \kappa)\lambda\rho)$, where A denotes the firm's equity capital, ρ_0 measures the extent to which agency costs limit the pledgeability of the firm's final payoff, and λ is the probability of a liquidity shock, ρI, that must be financed at an intermediate stage.

should be on the agenda for "making finance flows [...] consistent with climate-resilient development" (UNFCCC (2016)).[10]

The next section discusses our contributions to the related literature. In the remainder of this section, we further describe our analysis and discuss its external validity. By focusing on hotels in Austrian ski resorts, we use a sample of firms whose assets have a readily identifiable physical location linked to specific climate-related risks.[11] The sample includes 16,587 firms. We combine data about the firms' employment spells during the years 1977-2011 with high-resolution data about the ski resorts' snow levels during the years 1978-2006. An exploratory analysis shows that ski resorts at higher levels of altitude experienced pronounced increases in snow risk.[12] Our analysis exploits the variation in this risk across years and weeks of the skiing season. The high granularity of the data allows for using firm-year fixed effects as a control variables.[13] The fixed effects control for variation across years in firms' risk-taking when they commit to quasi-fixed labor costs, e.g. due to changes in firms' capital structures, or local labor market tightness. We thus obtain particularly clean estimates of the effect of labor productivity risk on employment.

While we focus on a rather special sample of firms, we consider an issue that is generally relevant given the view of Knight (1971) that firms are institutions insuring workers against transitory labor productivity shocks: The firms may

[10] See Krogstrup and Oman (2019) and Campiglio, Dafermos, Monnin, Ryan-Collins, Schotten, and Tanaka (2018) for surveys of the emerging literature regarding climate finance and financial regulation. For a discussion of "green" bank capital regulation, see HLEG (2018) and Thomä and Hilke (2018).

[11] Samples like this are commonly used in microeconometric analyses of effects of climate change. For a survey, see Dell et al. (2014).

[12] At above-median altitudes, snow risk increased by 42% during a period of 25 years (1982-2006). One advantage of our sample period ending in the year 2006 is that it excludes more recent years in which most Austrian ski resorts installed snow cannons in order to produce artificial snow.

[13] Our results come from weekly data. In fact, we report separate estimate for different parts of the skiing season. We thus even control for some within-firm-year variation. Below, we refer to the firm-year fixed effects as firm-season fixed effects because we distinguish between skiing seasons rather than calendar years.

themselves need some insurance against liquidity shocks.[14] To set the stage for analyzing this issue, we test whether the firms in our sample actually insure their workers against weather-induced labor productivity risk. If so, their employment should not depend on weekly variation in snow conditions. When we test this hypothesis, we find that the snow conditions do actually affect the ski hotels' employment during the ending weeks of the skiing season, but not during the starting weeks. These findings are consistent with evidence in Guiso et al. (2005) that firms fully insure their workers against transitory productivity shocks, but not against more permanent shocks. During the ending weeks of the skiing season, the snow-induced labor productivity risk is clearly a risk of permanent shocks. During the starting weeks, it instead is a risk of transitory shocks. With respect to the latter shocks, the ski hotels' employment appears to be quasi-fixed.

We next focus on the starting weeks of the skiing season. It turns out that, during these weeks, the ski hotels' employment responds to the risk of transitory snow shocks even though the shocks have no direct effects. This evidence results from a proxy for the snow risk in a ski resort during a given week (e.g., the week before Christmas) that measures the variation in this resort-week's snow conditions during the last five years.[15] This proxy represents information available prior to the start of a skiing season. It appears that the firms respond to this information when they enter into employment contracts: An increase in

[14] Financial constraints may in fact induce firms to use more flexible types of employment. This is analyzed in Caggese and Cuñat (2008) and follow-up papers. As discussed above, we control for such financial constraints by using firm-year fixed effects.

[15] The same measure is used in our explanatory analysis to document that ski resorts at higher altitudes experienced pronounced increases in snow risk during our sample period. Given these trends, the firms expectations about snow risk should depend on the snow conditions they observed during more recent years because the firms should be aware of the trends.

snow risk by one standard deviation reduces firm-level employment by about 3%.[16]

Our results regarding the effect of bank equity come from regressions in which we interact our proxy for snow risk with the average equity ratio of the banks in the vicinity of a ski resort. We use these interaction terms to test whether bank equity modulates the effect of snow risk on the ski hotels' employment during the starting weeks of the skiing season. The test yields first evidence that bank equity acts as a catalyst for the firms' risk-taking with respect to labor productivity risk induced by snow risk: The employment of firms in areas with less bank equity responds more negatively to snow risk. This effect is robust to extending our regressions by including other features of the banks close to a ski resort, e.g., their geographic diversification (branch networks).[17]

Our main evidence comes from instrumental variables (IV) estimates, addressing the problem that we cannot directly observe the extent to which snow risk induces labor productivity risk. This is a concern because our measures of bank equity may be correlated with cross-sectional variation in the extent to which our sample firms face labor productivity risk due to snow risk. The correlation could be negative (e.g., due to losses incurred by banks with borrowers in high-risk areas), or positive (e.g., due to bank-financed investments reducing hotels' exposure to snow risk). As a consequence, it could be inappropriate to interpret our OLS estimates as results regarding causal effects of bank capitalization on the extent to which labor productivity risk affects employment. Instead, we may be simply observing variation in the effect of snow risk on labor productivity risk.

[16] We find no evidence for a similar effect during the season's ending weeks. This is consistent with the evidence that snow risk during the latter weeks is borne by the hotels' workers since they simply get laid off when their productivity drops due to a lack of snow for skiing.

[17] See Levine, Lin, and Xie (2020) for a recent analysis of banks' geographic diversification on their funding costs.

The IV estimates are based on an institutional feature of the Austrian banking sector, i.e., that there are many regional banks that belong to banking groups with internal capital markets (e.g., the group of savings banks). We use the – exogenous – variation in the groups' aggregate equity capital as a proxy for variation in regional banks' equity capital.[18] Instrumental variables estimates reveal that this equity capital is indeed endogenous. We, however, again observe a weaker negative effect of snow risk on employment in areas with more bank equity, and we can now rule out that this is due to bank equity proxying for the extent to which snow risk causes exogenous labor productivity risk. Per basis point of bank equity above its mean, we observe a 1.25% reduction in the semi-elasticity of employment with respect to snow-induced labor productivity risk.[19]

We end this section by discussing the external validity of our results. As discussed above, the firms in our sample behave according to the predictions of models that have been validated at both the macro- and the micro-level. This is reassuring, but specific concerns about the external validity of our results arise because we focus on seasonal businesses in rural areas and a particular type of risk.

As seasonal businesses, ski hotels may enjoy a high degree of flexibility in adjusting their employment, but they may also face rather tight labor markets because they operate in rural areas. We therefore investigate the external validity of our results by testing for effects of labor market tightness. It appears that, in areas with high labor market tightness, the firms' employment responds particularly negatively to risk, and even more so if the local banks lack equity capital. This is consistent with the idea that bank equity affects firms'

[18] Endogeneity of the aggregate equity capital is of little concern since the banking business in any given ski resort accounts for a negligible share of any banking group's business. Differences between the groups in the variation of their aggregate capital affect ski resorts in different ways because the groups differ in their (aggregate) branch networks.

[19] The semi-elasticity equals -13% given the mean value of bank equity.

capacity to commit to quasi-fixed employment because employment should be more quasi-fixed in areas with tighter labor markets. The results suggest that our evidence is generally relevant for firms in industries and regions with tight labor markets.

A second concern arises because we may be analyzing effects of a labor productivity risk that is an unusually clear-cut risk of transitory shocks. This concern can be raised more generally with respect to labor productivity risk due to weather risk as a risk that is, by definition, one of transitory shocks. This risk actually affects many small firms in any economy, e.g., agricultural or construction businesses. If these firms rely on banks to obtain insurance against liquidity shocks, our results should in fact be useful for understanding an important role of banks in economic adaptation to changes in weather risk. In this respect, our evidence suggests that, by providing firms with liquidity insurance, the financial sector may be key to stabilizing employment if weather variability increases due to climate change.

The following section further discusses the related literature. Section 2 describes our research strategy. Section 3 presents institutional details of the industry we focus on. Section 4 describes our data sources and descriptive statistics. Section 5 presents our results. Section 7 concludes.

1.1 Related literature

Our analysis tests the foundations of macro-finance models in which firm-level employment decreases if the volatility of worker productivity increases. Arellano et al. (2019) (discussed above) and Quadrini (2017) analyze this effect based on models in which employers take risk by committing to employing workers whose productivity is uncertain.[20] The models explain employment

[20] Other effects of the interaction of uncertainty with financial market frictions are analyzed for example in Christiano, Motto, and Rostagno (2014), Gilchrist, Sim, and Zakrajsek (2014), Alessandri and Mumtaz (2017), Lhuissier, Tripier, et al. (2016), Alfaro, Bloom, and Lin (2018).

fluctuations at the macro-level as effects of changes in the risk of productivity shocks that have no *direct* effects on employment. The quasi-fixed nature of employment is key because it implies that employers take risk by hiring employees.[21] Financial market frictions affect this risk-taking and, hence, the way employment responds to changes in risk. We provide corroborating firm-level evidence, making sure that we really measure effects of changes in the risk of shocks which have no direct effects on employment (because they are transitory shocks, like the shocks in the models of Arellano et al. (2019) and Quadrini (2017)).

Our analysis thus connects two empirical literatures that analyze related phenomena. The first literature analyzes direct effects of shocks on employment, while the second analyzes effects of risk.[22] The papers in the first literature show that different types of shocks have different effects.[23] This implies that the effects of a risk on employment can only be interpreted conditional on the results of a prior analysis of the direct effects of the shocks associated with the risk. Our paper is the first contribution that uses this research strategy. This is clearly key for testing the micro-foundations of the employment dynamics in the macro-finance models of Arellano et al. (2019) and Quadrini (2017). We provide the first evidence that quasi-fixed employment responds to changes in risk, making sure that we actually analyze a risk of shocks for which employment is quasi-fixed.[24]

[21] For contributions regarding the quasi-fixed nature of labor costs, see for example Oi (1962) and Hamermesh (1989).

[22] A survey of the first literature appears in Pagano (2019). For a recent contribution to the second literature and related references, see Alnahedh, Bhagat, and Obreja (2019).

[23] Guiso et al. (2005) propose a convincing strategy for identifying effects of transitory and persistent shocks, but they do not analyze whether employment responds to variation in the risk of these shocks. The same identification strategy has been used in follow-up research, e.g., by Cardoso and Portela (2009) , Kátay (2016), Guertzgen (2014) and Ellul, Pagano, and Schivardi (2018).

[24] In fact, it is only this risk for which we find statistically significant effects of the risk on employment. More generally, the effects of risk on employment depend on the extent to which firms can adjust their employment in response to shocks. This must be considered in order to meaningfully measure effects of risk on employment.

To the best of our knowledge, we also report the first evidence that banks' equity capital affects the response of (quasi-fixed) employment to changes in risk. The evidence results from variation across relatively local banking markets.[25] This is consistent with the notion that small firms' access to banks is restricted by exogenous geographical constraints since a firm's proximity to a bank affects the banks' access to soft information about the firm's credit-worthiness (Petersen and Rajan (2002), Berger et al. (2005)). This idea is central to the literature on relationship banking.[26] By measuring effects of variation in bank equity across local banking markets (rather than across firms' actual housebanks), we avoid potential biases due to endogenous matching of firms and banks.[27] Moreover, our market-level measures of bank equity proxy for firms' ability to obtain financing through relationships to multiple local banks.[28] We

[25] We thus complement the analysis of Quadrini (2017) regarding effects of more aggregate variation in banks' liabilities.

[26] For examples, see Petersen and Rajan (2002), Degryse and Ongena (2005), Agarwal and Hauswald (2010), and Hauswald and Marquez (2006). For recent evidence, see Nguyen (2019). Nigro, DeYoung, and Glennon (2008) find that loan default rates increase in the distance between banks and borrowers. The validity of distance between banks and borrowers as an instrument for relationship formation is also discussed in Bharath, Dahiya, Saunders, and Srinivasan (2011). For a formal definition of relationship banking, see Boot (2000). Surveys of the literature appear in Drucker and Puri (2007), Strahan (2008) , Freixas and Rochet (1997), Degryse, Kim, and Ongena (2009), and Srinivasan (2014)

[27] Schwert (2018) reports evidence that more bank-dependent firms borrow from banks with more equity capital. This builds on evidence that such banks can provide firms with a more stable access to credit/liquidity (Bolton, Freixas, Gambacorta, and Mistrulli (2016) and Beck, Degryse, De Haas, and Van Horen (2018)). Bouwman (2019) surveys the literature on bank liquidity creation.

[28] With multiple business relationships to banks, firms' access to (re-)financing may be more secure with respect to the risk that banks' lending is affected by bank-level problems. See Guiso, Detragiache, and Garella (2000), Carletti (2004), and Carletti, Cerasi, and Daltung (2007).

also test for effects of the number of banks in an area,[29], the market share of small banks,[30] and banks' geographic diversification.[31]

The response of employment to changes in the banking landscape and credit supply is also analyzed in a number of other papers, e.g., Chodorow-Reich (2013), Benmelech, Bergman, and Seru (2015), Banerjee, Gambacorta, and Sette (2017), Bentolila, Jansen, and Jimenez (2017), and Nguyen (2019). To the best of our knowledge, none of these papers attempt to measure effects of financial frictions on the way employment responds to changes in labor productivity risk.

2 Research strategy

Our analysis can be motivated by the idea that firms' expectations about their access to liquidity insurance determine their risk-taking with respect to risks that cause liquidity needs (Holmström and Tirole (1998)). We analyze the risk-taking firms engage in when they hire workers, promising them pay before the workers generate uncertain revenues. This is based on an implicit assumption (which will be tested), i.e., that the firms actually commit to paying their workers, rather than sharing the risk with them. Under this assumption, a firm's wage bill is quasi-fixed, determined by the number of workers of the firm.

[29] Competition between banks can affect relationship lending and banks' screening of credit applicants. Theoretical analyses include Broecker (1990), Petersen and Rajan (1995), Dinc (2000), Yafeh and Yosha (2002), Boot and Thakor (2000), Marquez (2002), Dell'ariccia and Marquez (2004), and Hauswald and Marquez (2006). Empirical work include Petersen and Rajan (1995), Elsas (2005), Black and Strahan (2002), Degryse and Ongena (2007), Rice and Strahan (2010), Presbitero and Zazzaro (2011), Ogura (2012), and Marco and Petriconi (2019).

[30] Small banks may be better at using soft information in their lending decisions, as posited in Stein (2002). Related evidence appears for example in Cole, Goldberg, and White (2004), Berger, Demirguc-Kunt, Levine, and Haubrich (2004), Liberti and Mian (2009), Cerqueiro, Degryse, and Ongena (2011), Agarwal and Hauswald (2010), Skrastins and Vig (2018) and Berger, Minnis, and Sutherland (2017). The literature is surveyed by Liberti and Petersen (2019).

[31] Banks' branch networks clearly determine banks' ability to cope with local shocks. Banks' geographic diversification also affects their ability to monitor borrowers (Winton (1999), Berger et al. (2004)). Related evidence appears for example in Chong (1991), Demsetz and Strahan (1997), DeLong (2001), Acharya, Hasan, and Saunders (2006), Akhigbe and Whyte (2003), Deng and Elyasiani (2008), Goetz (2012), and Goetz (2018).

With e employees, a firm has to finance a liquidity shock of $\max(w - \rho, 0)e$, where we is the firm's wage bill, and ρe is the total revenue generated by the employees, determined by a random variable ρ that realizes after the firm has committed to the wage bill.

More generally, the number of employees may affect the riskiness of the revenue per employee due to (dis-)economies of scale. In our sample, this happens because, as seasonal businesses, the firms regularly experience capacity constraints determined by their fixed assets. As the number of workers in a firm increases, the capacity constraints will at some point limit the firm's exposure to labor productivity risk due to exogenous demand shocks. We will therefore focus on effects of demand shocks during periods when the capacity constraints are clearly not binding. Moreover, we will focus on the firms' employment of a rather homogeneous group of blue-collar workers, i.e., their staff for waiting tables, cleaning rooms, and other services directly related to ski tourism. The productivity of these workers depends on ski tourists' demand, and weather risk causes labor productivity risk.

A firm in our sample employs workers that generate a revenue $\rho = f(s, X)$, where s is an exogenous ("snow") shock and X denotes a set of variables that determine the firm's exposure to the shock, i.e., the extent to which the firm is affected by a given shock. The function f describes the risk a firm takes when it increases the number of its workers and, thus, its exposure to snow-induced variation in labor productivity. We want to measure how this risk-taking depends on characteristics of the banking landscape in the vicinity of a firm. To do so, we must address two identification problems.

The first problem is that snow risk may be correlated with choice variables included in the set X. We resolve this problem by using highly granular social security data in order to analyze firms' weekly employment with a focus on effects of variation in snow risk across weeks of the skiing season. Given this focus on short-run variation in risk, we can assume that any choice variables in X are quasi-fixed within firm-years (skiing seasons). This assumption is realistic, e.g., with respect to investments in fixed assets that would reduce the firms' exposure to snow risk.[32]

The second identification problem concerns the causal effect of the banking landscape on the way firms' employment responds to risk. To measure this effect, we will use the following regression

$$\ln(ED_{i,t,T}) = \beta_0 \sigma_{j(i),t,T} + \beta_1 \sigma_{j(i),t,T} \times b_{j(i),T} + \gamma Z_{i,t,T} + \alpha_{i,T} + \alpha_t + \epsilon_{i,t,T}, \quad (1)$$

where T indexes years (skiing seasons), t indexes weeks, and i indexes firms in regions (ski resorts) $j(i)$. The coefficient β_0 measures effects of weather risk $\sigma_{j(i),t(T)}$ on firm i's employment $ED_{i,t,T}$ (in employee-days), and the coefficient β_1 measures how the semi-elasticity of employment with respect to weather risk changes in characteristics of the local banking sector, $b_{j(i),T}$. For details regarding these variables, see Section 3. As discussed above, we focus on effects of short-run variation in weather risk by including firm-year fixed effects $\alpha_{i,T}$ and week fixed effects α_t.

The identification problem concerns the causal interpretation of the coefficient β_1, i.e., the causal effect of bank characteristics $b_{j(i),T}$ on the elasticity of employment with respect to weather-induced labor productivity risk. Lacking suitable measures of labor productivity, we cannot directly measure the extent of labor productivity risk due to weather risk.[33] We must therefore rule out that the variable $b_{j(i),T}$ proxies for the extent to which weather risk causes labor productivity risk. This is a possibility because the variable $b_{j(i),T}$ may

[32] For example, many ski hotels feature wellness areas that their guests use when they are not out skiing. It seems safe to assume that hotels would not add a wellness area during the skiing season since the off-season is a better time for the requisite construction work.

[33] The regression (1) will be estimated based on a linked employer-employee dataset that contains no firm-level balance sheet data.

be correlated with omitted variables affecting firms' exposure to weather risk, $X_{i,T}$.[34]

We address the second identification problem with respect to regressions in which the variable $b_{j(i),T}$ measures local banks' equity capital buffers. Our approach is based on an institutional feature of the Austrian banking system, i.e., that it is a "three-pillar" banking system composed of three groups of banks, i.e., private banks, savings banks, and cooperative banks. The last two groups contain many small banks with geographically concentrated branch networks. These small banks cooperate in group-specific internal capital markets, including equity capital markets.[35] Variation in the groups' aggregate equity capital can therefore be used as an instrument for the regional banks' equity. For further details regarding this instrument and our measures of regional banks' equity, see Section 3.2. Validity of the instrument ensures that we can use the ratio β_1/β_0 to measure the effect of bank equity on the semi-elasticity of employment with respect to exogenous labor productivity risk due to snow risk.[36]

3 Institutional background

Our analysis is based on a sample of firms exposed to a particularly quantifiable and exogenous risk affecting the productivity of their employees, i.e., weather risk. We now describe the firms' industry, with a focus on its financing and its labor market. Moreover, we describe the Austrian banking sector.

[34] As discussed above, we treat this exposure as a quasi-fixed variable which does not vary across weeks t.

[35] It is clear that the banks obtain their equity capital on group-specific internal capital markets because ownership linkages are much more prevalent within than across groups. During our sample period, all groups had group-specific deposit insurance and access to external equity capital markets through their lead banks.

[36] Suppose that bank equity modulates the effect of labor productivity risk $\xi_{i,t(T)}$ on log employment: $\ln(e_{i,t(T)}) = \theta_0\xi_{i,t(T)} + \theta_1\xi_{i,t(T)}b_{j(i),T} + \ldots$. Moreover, suppose that snow risk causes labor productivity risk: $\xi_{i,t(T)} = x_i\sigma_{j(i),t(T)} + \nu_{i,t(T)}$, where x_i is firm i's exposure to snow risk and $\nu_{i,t(T)}$ is an error. By using a measure of bank equity uncorrelated with this error and x_i, we can assume that the ratio θ_1/θ_0 equals the ratio β_1/β_0 of the coefficients in regression (1).

3.1 The Austrian hotel industry

The Austrian hotel industry consists mostly of small family-owned firms: Doerflinger, Doerflinger, Gavac, and Vogl (2013) report that such firms account for 93% of all firms in the industry. Given that the larger hotels tend to operate in urban areas, these firms are not contained in our sample because we focus on hotel businesses in ski resorts and exclude firms in towns with a population larger than 20,000. As a consequence, the fraction of family-owned businesses in our sample should be even higher than 93%.[37]

As family-owned businesses, the firms in our sample typically obtain their outside financing from local banks. When they borrow from the banks, they often use real estate as collateral, i.e., their buildings and land. In some cases, the owners are also personally liable for their firms' debt.[38] If the firms receive outside equity, it is typically from relatives.[39]

Our sample includes all hotel businesses operating in Austrian municipalities connected to one of Austria's ski resorts.[40] The firms are subject to demand shocks due to weather risk. Töglhofer, Eigner, and Prettenthaler (2011) analyze panel data about 185 Austrian ski resorts and find that an unexpected change in snow conditions by one standard deviation changes the number of

[37] We have no data about the ownership structure of the firms in our sample. Data about the size of hotels is contained in Statistik Austria (2018). At the end of our sample period (winter 2006), the average Austrian hotel business had an accommodation capacity of 17.9 beds. This average is higher than the average size of hotels in regions with a strong focus on ski tourism, e.g., Tyrol (15.7 beds) or Vorarlberg (13.3 beds).

[38] A case like this is described in Giroud, Mueller, Stomper, and Westerkamp (2011). This case concerns a financially distressed hotel.

[39] Loans from relatives are also treated as equity investments under Austrian bankruptcy law.

[40] We use the following list of Austrian ski resorts: https://de.wikipedia.org/wiki/Liste_der_Skigebiete_in_ÃŰsterreich.

tourists' overnight stays in nearby hotels by 0.6-1.9%.[41] Not surprisingly, snow risk also affects the employment of the firms in our sample. In Figure 1, we plot an average firm's employment over the weeks of the skiing season. We measure employment in terms of person-days, as discussed in Section 4.1. The solid line shows the average total employment and the dashed line plots the average employment of temporary employees.[42] We plot the variation in these averages over the weeks of the skiing season, i.e., between week 47 and week 15 of the subsequent year.[43] The plot reveals that the hotels' employment exhibits strong seasonal variation, driven by their hiring and firing of temporary employees. In our empirical analysis, we will focus on these employees because their employment is clearly associated with ski tourism.

Figure 2 contrasts the plot in Figure 1 with plots depicting variation in ski resorts' snow conditions across the weeks of the skiing season. As discussed in Section 4.1, we focus on the risk that the snow conditions may be too bad for skiing since there is not enough snow. We measure this risk based on a dummy variable indicating "ski weeks", defined as weeks in which the average snow level in a ski resort exceeded 15 centimeters for a majority of days. The solid line plots the probability with which, across all ski resorts and years in our sample, a given week (e.g., the second week of December) is classified as a ski week. The dashed line plots the standard deviation of this ski week indicator during the sample period. It appears that the variation in the snow conditions

[41] In unreported regressions with resort and year fixed effects, we find similar effects on tourists' overnight stays in the resorts included in our sample. Töglhofer et al. (2011) measure snow conditions in terms of the number of days in which the snow depth at a resort's mean altitude exceeds either 1 centimetre or 30 centimetres. As discussed in Section 4.1, we use a cut-off of 15 centimetres, following Giroud et al. (2011). Like Töglhofer et al. (2011), we use data about natural snow levels. During our sample period, there were hardly any snow cannons in Austrian ski resorts. As a consequence, data about natural snow levels can be used to measure the snow conditions relevant for skiing.

[42] As discussed in Section 4.1, we focus on temporary workers employed by the firms in our sample during the skiing season.

[43] These start and end dates are based on information about ski lifts' opening and closing dates. See Section 4.1.

coincides not only with tourists' demand for accommodation (Töglhofer et al. (2011)), but also with the employment variation depicted in Figure 1.

In our analysis, we will focus on the variation in employment during the periods marked by the two corridors of red lines in Figure 1, i.e., the starting and ending weeks of the skiing season. We thus focus on weeks during which labor productivity may respond to snow-induced variation in tourists' demand for accommodation since the hotels are not booked out.[44] We will test whether, during these weeks, the hotels' employment depends on the snow conditions in the nearby ski resorts. These tests will reveal whether the hotels adjust their employment in response to demand shocks caused by changes in ski resorts' snow conditions that occur during the skiing season. If the employment is quasi-fixed, it should not depend on snow "news" realized during the season, but it may depend on snow risk and the expected snow conditions.

In the remainder of this section, we discuss institutional details concerning the ski hotels' risk management with respect to weather-induced demand- and labor productivity risk. With respect to demand risk, the main risk-management tools are the hotels' cancellation and pricing policies. While booking platforms nowadays allow hotels much flexibility in adjusting their prices, these platforms were not yet common during our sample period.[45] This limited the ability of the hotels to respond to within-season demand shocks by adjusting their prices. Instead, most hotels set their prices in advance of the skiing season by specifying two prices per room, i.e., a high-season price and an off-season price. Given these prices, tourists would typically book their rooms several months in

[44] Figure 1 shows that, during the high season, employment is indeed rather constant.

[45] For example, consider the most popular platform, i.e., www.booking.com. While this platform was founded in the Netherlands in 1996, it only started to operate in Austria in week 27 of 2006, i.e., at the very end of our sample period. Data from Google trends show zero traffic in Austria before that date. The overall share of total online travel sales in Europe was only 5.5% in the year 2003 Eurostat (2006).

advance.[46] In the event of a lack of snow, tourists would cancel their bookings subject to cancellation policies specified in industry-wide terms of trade.[47] The cancellation fee was/is typically a fraction of the total price of a booking, increasing in the lateness of the cancellation. The standard fee schedule specifies a fee of 70% for cancellations with a notice period of less than 1 month, but the fee is 90% for cancellations less than one week before the first night booked.[48] This fee schedule suggests that tourists' demand for accommodation during a given week of the skiing season should depend not only on the current snow conditions, but also on those lagged by one week because tourists can avoid a substantial rise in cancellation fees by canceling one week before arrival.

We next turn to the hotels' contracting with their workers. They typically employ few permanent workers (mostly members of the owner family) so that temporary employees constitute most of their workforce during the skiing season. Under Austrian labor law, these workers ("Saisoniers") sign fixed-term contracts with the firms. Such a contract is only valid, if it contains a start and end date stated as an exact calendar day.[49] It is not legal for a firm to unilaterally fire a temporary worker before the worker's contract ends. It is, however, relatively easy for firms and workers to bilaterally extend employment relationships after the end of employment contracts. As a consequence, many of the employment contracts specify ending dates before the likely end of the skiing season. The contracts' starting dates are instead chosen so that the workers have sufficient time to move to the ski resort villages before they

[46] Even in 2015, 66% of Austrian hotels' bookings are made more than one month in advance WKO (2016). In ski resorts, this percentage should be higher because of the missing short-run bookings by business travelers.
[47] The terms of trade are drafted by lawyers of the Austrian Hotel Association. By using these terms of trade, the hotels avoid costs of legal expertise.
[48] This fee schedule has remained unchanged for decades. The 2006 fee schedule is depicted in the Online Appendix.
[49] A contract "starting when the snow arrives and ending when the snow is gone" would be considered as a permanent contract Steuerberatung (2018).

have to start working. Hiring workers on the spot is limited by local labor market tightness since the villages are typically rather small.[50]

Are there other forms of risk-sharing with workers, e.g. in terms of hours worked or wage changes? While the workers receive fixed hourly wages, changes in hours would be possible, in principle. To assess the extent to which snow risk affects workers' hours, we can compare the variance of wages that workers received during the two parts of a skiing season before/after the turn of the calendar year.[51] Given that the season's starting weeks are in the first part, snow risk should increase the wage variance during this part of the season if the risk affects workers' hours. We however see no evidence for this effect.

In our empirical analysis, we will analyze the extent to which snow risk affects the employment of the firms in our sample. The firms' ability to commit to quasi-fixed labor costs may depend on their access to insurance against weather risk. Nowadays, the hotels obtain most of this insurance as a consequence of the extensive use of snow cannons in Austrian ski resorts. The vast majority of these devices were installed after the end of our sample period.[52] During this period, the hotels also had no other ways of obtaining direct insurance against weather risk. Markets for suitable weather derivatives do/did not exist and insurance companies only offer bad-weather-insurance for specific outdoor events (e.g., ski races) which typically take place during the high-season, rather than the starting and ending weeks of the skiing season. Given our focus on these weeks, we can safely assume that the firms in our sample had no options to obtain explicit insurance against weather risk.

[50] For evidence regarding effects of labor market tightness, see Section 6.2.

[51] This is possible because we have data about workers' total annual income (but no more granular data).

[52] The rapid growth in the use of snow cannons after our sample period (1978-2006) can be illustrated using the following numbers: In 2007, there were 3100 snow cannons in all of Europe, while in 2015 slightly more of these devices were used in just three Austrian ski resorts. See https://www.sn.at/wiki/Beschneiungsanlage. Unfortunately, we do not know any comprehensive historic data about snow cannons installed in Austria.

3.2 The Austrian banking industry

Like Germany, Austria has a "three-pillar" banking sector, consisting of private banks (stock corporations), savings banks, and cooperative banks. The groups of savings banks and cooperative banks operate within group-specific institutional frameworks, featuring joint supervisory institutions and deposit insurance, as well as lead banks that provide the groups with access to the wider financial markets. Within-group competition between banks is quite limited, but there is a healthy level of between-group competition. In terms of population size per bank branch, Austria remains among the most competitive countries in the European Union.[53] In terms of total assets, the savings banks have a market share of about 20% while the cooperative banks have a share of about 30% (Bülbül, Schmidt, and Schüwer (2014)).

In terms of ownership links, the groups of savings and cooperative banks are separate parts of the Austrian banking sector, but there are complex cross-ownership structures within the groups. The groups feature internal equity capital markets. For example, the savings banks' lead bank, Erste Bank, is partly owned by other savings banks. The internal equity markets are also key to resolving cases of financial distress. Distressed banks are typically saved through mergers with other banks in the same group.

As in Germany, the banks within a group also assist each other in their lending, e.g., by making joint loans.[54] This practice complements the groups' internal equity markets. To avoid that a lack of equity capital constrains an individual bank's lending, the bank can either obtain equity capital from other banks in the same group or make a joint loan together with the other banks. In the latter case, the banks' joint equity capital must be sufficient in order to meet regulatory equity capital requirements. Throughout our sample period, the

[53] See Table 9.2 in ECB (2017).
[54] For further discussion with respect to German savings banks, see DSGV (2012).

Austrian banks were subject to equity capital requirements according to Basel I.

4 Data and descriptive statistics

4.1 Data

We construct a data set in which one observation corresponds to a firm-week. The focus is on calendar weeks of the skiing season. In each season T, the starting weeks are the four weeks 47-50 of the calendar year in which the season starts. These weeks lead up to the start of the high season, i.e., the Christmas holidays. The skiing season's ending weeks are defined as the four weeks 11-15 of the following calendar year.

Employment data The employment data come from the Austrian Social Security Database (ASSD). We start with the universe of employment relations (spells) in the Austrian tourism sector between 1977 and 2011: 10,316,391 employment spells between 1,603,556 distinct employees and 136,735 firms. 47.5% of these spells concern employees working in ski tourism. To identify these employment spells, we use the above-stated definition of the skiing season and only consider spells in municipalities featuring at least one ski lift within a radius of 10 km, excluding cities with more than 20,000 inhabitants. Within this group, most of the workers are in the hotel industry (62.9%), while the rest work in other accommodation, or in food and beverage services.[55]

Given that we have no data about hours worked, we focus on the days during which an employee was employed by a firm. The sample of firms includes all employers that appear in the employment spells associated with ski tourism,

[55] For simplicity, we will refer to all of these workers as workers employed by hotels. This makes sense because most hotels feature restaurants and bars that operate in much the same way as other restaurants and bars in ski resorts.

as defined above. To measure a firm's number of employment, we first define a dummy variable, denoted as $E_{w,i,d}$, which indicates whether worker w was employed at firm i on calendar day d. We next use this dummy to measure "employment days" at the firm-week level, defined as follows:

$$ED_{i,t,T} = \sum_{d \in D(t,T)} \sum_{w} E_{w,i,d}, \tag{2}$$

where t indexes weeks, T indexes skiing seasons, and $D(t,T)$ is the set of calendar days in a particular week. We construct two versions of the above-stated variable for each of the tourism businesses in the ski resorts. The first variable measures firm i's total employment days based on all of our data about employment spells involving this firm. The second variable is the dependent variable of our regressions. It measures employment days based on the employment spells associated with ski tourism, as defined above. Figure 1 plots averages of these two variables across all firms and skiing seasons.

We also construct a variable measuring the level of labor market tightness (LMT) within firm i's county $c(i)$ in year T. LMT is defined as the inverse of the county's unemployment rate, i.e. $(1 - \text{unemployment rate}_{c(i),t})$.

Snow data We use the same snow data as Töglhofer et al. (2011). The data come from the Austrian Meteorological Office (AMO). The AMO provided us with 1×1 km grid data containing daily information on snow depth, based on a snow cover model using air temperature and precipitation data (Beck, Hiebl, Koch, Potzmann, and Schöner (2009)) as inputs. The model has been used to generate natural snow data for the years 1973-2006. The data can be used to measure the snow conditions relevant for skiing because, before 2006, there were few snow cannons in Austrian ski resorts.[52]

We match the snow data to municipalities based on the coordinates of all ski lifts within a 10 kilometer radius around the geographic center of a municipality's area. This radius defines the ski resort $j(i)$ around a firm i, based on the municipality key of the firm. To determine the snow conditions in this ski resort, we consider the center of each ski lift in the resort and average the snow levels at the closest grid points using our gridded snow data. Given a resort's average snow levels for each day of our sample period, we define a snow-week dummy that equals one during weeks in which the average snow level exceeded 15cm on a majority of days.[56]

Figure 3 illustrates our mapping of ski lifts to municipalities for the municipality of Lech am Arlberg, a well known resort in the Austrian state of Vorarlberg. The dashed circle is at a radius of 10 kilometers around the center of Lech. To measure the snow conditions around Lech, we consider all ski lifts marked by red lines. The grid of points shows the locations for which we have snow data. For each ski lift, we use the data for the grid point closest to the center of the line representing the ski lift.

In our empirical analysis, we will distinguish between two types of information about the snow conditions in ski resorts, i.e., information available before the start of the skiing season, and "news" that arrive during the season. The first type of information includes the expected snow conditions in ski resorts, and a measure of snow risk. As discussed above, we focus on whether the snow conditions allowed for skiing, using our snow dummy to indicate a sufficient level of snow. To measure the expected snow conditions during week t in season T, we compute the average of the snow-week dummy during the same week of the previous five years. Snow risk is defined in a similar way, based on the standard deviation of the snow-week dummy. The formal definitions are

[56] In choosing the 15cm cutoff, we follow Giroud et al. (2011).

as follows:

$$\text{Expected snow}_{j,t,T)} = \frac{1}{5}\sum_{n=1}^{5} \text{Snow week}_{j,t,T-n)}, \tag{3}$$

$$\text{Snow risk}_{j,t,T} = \sqrt{\frac{1}{5}\sum_{n=1}^{5}(\text{Snow week}_{j,t,T-n} - \text{Average snow}_{j,t,T})^2}, \tag{4}$$

where j indexes ski resorts. The sums are based on five year's of data prior to a skiing season T, i.e., the data about a week t of the five previous skiing seasons. The above-stated definitions thus allow for variation over time in our measures of expected snow and snow risk. In fact, climate change is likely to affect the first and second moments of the distribution of snow fall. Below, we document that the snow variables defined above indeed exhibit significant long-term trends.

We also use a measure of snow "news", defined as the difference between the snow-week dummy and expected snow:

$$\text{Snow news}_{j,t,T} = \text{Snow week}_{j,t,T} - \text{Expected snow}_{j,t,T}. \tag{5}$$

Banking data Balance sheet data about Austrian banks are available from the Austrian Central Bank (OeNB). The data start in the year 1998 and contain unconsolidated balance sheets of all banks operating in Austria. To map the data to the firms in our sample, we use data about the branch networks of Austrian banks. This second type of data also comes from the OeNB.

The mapping is again based on the municipality keys of the firms in our sample. We first assign to each firm i the coordinates of the center of the area associated with the firm's municipality. Then, we identify all bank branches within a radius of 20 kilometers around these coordinates. This defines the banking landscape around firm i. Given this area, we can define a number of variables. The first variable is the average equity ratio of the banks in the vicinity of firm

i:

$$\text{Bank Equity}_{i,T} = \sum_b \frac{m_{i,b,T}}{M_{i,T}} \times \frac{\text{Total equity}_{b,T}}{\text{Total assets}_{b,T}}, \tag{6}$$

where the fraction is the equity ratio of bank b in year T, and we compute a weighted average of the equity ratios of all banks. For bank b, the weight is the number of its branches in the area of firm i divided by the total number of bank branches in this area, $m_{i,b,T}/M_{i,T}$.

As discussed in Section 2, we use specific measures of the equity capital of the groups of savings banks (Sparkassen) and cooperative banks (Volksbanken and Raiffeisenbanken). We refer to these banks as "regional banks" and denote the set of regional banks by $\mathcal{R}$. The average equity ratio of the regional banks is defined as follows:

$$\text{Bank Equity}^{reg}_{i,T} = \sum_{b\in\mathcal{R}} \frac{m_{i,b,T}}{M^{reg}_{i,T}} \times \frac{\text{Total equity}_{b,T}}{\text{Total assets}_{b,T}} \tag{7}$$

where $M^{reg}_{i,T}$ denotes the number of regional banks in the area of hotel i.

The above-stated measures of bank equity result from bank-level balance sheet data. In addition, we measure bank equity at the level of banking groups. The resulting measure of bank equity will be used as an instrument for the regional banks' equity, defined above. It is defined as follows:

$$\text{Bank Equity}^{grp,reg}_{i,T} = \sum_{b\in\mathcal{R}} \frac{m_{i,b,T}}{M^{reg}_{i,T}} \times \frac{\text{Total equity}^{grp}_{b,T}}{\text{Total assets}^{grp}_{b,T}} \tag{8}$$

where Total $\text{equity}^{grp}_{b,T}$ denotes the aggregate equity capital of the group of banks associated with bank b (i.e., the sum of the equity capital of all member banks of this group), and Total $\text{assets}^{grp}_{b,T}$ denotes the group's aggregate assets.

While the last two measures of bank equity are only available for the regional banks, we also define a variable which combines the group-level equity ratios with the equity ratios of banks that are not part of a group. This variable is denoted as Bank Equity$^{grp}_{i,T}$. It is defined in a similar way as the variable in expression (6), but we replace the equity ratios of all regional banks in firm i's area by the group-level equity ratios of these banks' groups.

Besides equity ratios, we use two other variables describing the local banking landscape around firm i: The number of banks in the vicinity and a measure of the extent to which the banks operate on a nationwide scale, *Branch diversification*. The number of banks is simply defined as the number of distinct banking groups which operate in the 20 kilometer radius around the center of a postal code area. A bank's *Branch diversification* is defined as the euclidean distance of all branches to a hypothetical mid-branch. To compute aggregate measures of banks' *Branch diversification*, we use the following approach:

$$\text{Branch diversification}_{i,T} = \sum_b \frac{m_{i,b,T}}{M_{i,T}} \sum_{n \in b} \sqrt{(lat_{n,b,T} - \overline{lat_{b,T}})^2 + (lon_{n,b,T} - \overline{lon_{b,T}})^2} \tag{9}$$

where n indexes the branches of bank b. The hypothetical mid-branch location is given by $\overline{lat_{b,T}}$ and $\overline{lon_{b,T}}$ which are defined as the average latitude and longitude of all of bank b's branches in year T.

Following Berger and Bouwman (2009), we also construct a variable characterizing the liquidity creation capacity of banks operating in the 20 kilometer radius around a firm i. This variable is defined as follows:

$$\begin{aligned}\text{Liq}_{i,T} = &\sum_b \frac{m_{i,b,T}}{M_{i,T}} \Big(\frac{1}{2}(\text{Illiquid assets}_{b,T} + \text{Liquid liabilities}_{b,T}) \\ &- \frac{1}{2}(\text{Liquid assets}_{b,T} + \text{Iliquid liabilities}_{b,T})\Big)\end{aligned} \tag{10}$$

4.2 Descriptive statistics

We next discuss the descriptive statistics of our main variables. Table 1 concerns our snow variables, i.e., our dummy variables indicating snow days and snow weeks, as well as the variables measuring expected snow and snow risk, as defined in expressions (4). While the dummy variables are based on the entire period for which we have snow data (1978-2006), the latter variables are measured over the period 1983-2007 (because each data point of these variables is based on the past 5 years of snow data). For each variable, we report the extent of its variation between and within ski resort-years. The within-variation in snow risk is key to our research strategy for measuring effects of exogenous labour productivity risk on firm-level employment. The descriptive statistics show that the within-variation accounts for a substantial part of the overall variation in snow risk and expected snow.

Table 3 reports descriptive statistics regarding our measures of firm-level employment in employment days of all employees and ski employees. Employment days are defined in expression (2). We separately report summary statistics for the entire winter season, the starting weeks and the ending weeks of the winter season. These statistics complement Figure 1 which shows the variation in employment days over the weeks of the skiing season. Both in terms of number of employees and employment days, temporary employment accounts for roughly 50% of total employment of the firms in our sample. In our analysis, we do analyse the extensive margin of running the firm in certain weeks, which explains the existence of zero employees in certain weeks of the season.[57]

Table 4 reports descriptive statistics about variables which do not vary within the winter season, i.e. variables which characterize the local banking landscape and altitude. The average firm is located at around 1000 meters above sea

[57] However, the firm must be open, i.e. employ workers, for at least a week during the winter season in order to be included in our sample.

level. Concerning the local banking landscape, on average there are about 6 distinct banks located in the vicinity of our firms. The mean of equity ratio of these banks is roughly the same at 8% for (i) the universe of banks and the subset of regional banks, and (ii) bank-level balance sheet data and group-level consolidated balance sheet data. Not surprisingly, the standard deviation of group-level consolidated equity ratios is relatively lower when compared to unconsolidated equity ratios. On average, the banks around our firms span a branch network of 2000 kilometers, with some banks being very local while other banks operating nationwide.

5 Main results

5.1 Weather risk and employment

As discussed above, our research question concerns firms' risk-taking when they employ workers whose productivity depends on the weather. Given this focus, we start our analysis by testing whether the firms in our sample share risk with their workers by adjusting their employment in response to weather realizations. As hotels in ski resorts, they could be responding to changes in the resorts' snow conditions that affect tourists' demand for accommodation during a skiing season. In addition, their employment could depend on information about snow conditions that the firms obtained before the start of the season. The latter information may change the firms' pre-season expectations about the expected snow conditions as well as snow risk. For example, the firms could use this information in order to update their expectations with respect to effects of climate change. The specifications of our snow variables allow for this updating of expectations because we they are based on 5-year rolling windows of data.

We start by documenting that our snow variables are indeed subject to significant long-term trends because the snow conditions in Austrian ski resorts have been changing over time. Table 2 presents regressions of our snow variables (defined in expression (4)) on calendar years and ski resort-week fixed effects. The fixed effects pick up differences between ski resorts in the typical extent and timing of snowfall. Given our interest in long-term trends, we use all available snow data, including years for which we have no employment or bank data. The data cover the period 1983-2007.[58]

We find that mean snow decreased over time, while snow risk increased. While the strength of the former trend decreases in the altitude of ski resorts, that of the latter trend increases in altitude. We measure altitude both in terms of standard deviations (across ski resorts) and in terms of a dummy indicating ski resorts at above-median altitude. In addition, we distinguish between the starting and ending weeks of the skiing season, as well as the rest of the season (as an omitted category). With respect to the starting (ending) weeks, we see weaker (stronger) negative time trends in mean snow. Snow risk increased particularly strongly during both the starting and ending weeks, and even more so at higher levels of altitude.

All in all, the estimates suggest the existence of long-term trends worsening the snow conditions in Austrian ski resorts. Ski resorts at higher levels of altitude were subject to particularly strong increases in snow risk. At above-median altitudes, snow risk increased on average (across all weeks) by 8.6% over the 25 years 1983-2007. This number implies an increase in snow risk of more than 40% relative to its 1982 mean in the higher 50% of ski resorts, which was 20.7% (across all weeks).

[58] While our snow data start in 1978, we need the first five years of data to compute the value of the dependent variables of our regressions in the year 1983. We cluster the standard errors at the level of ski resorts to address the problem that consecutive years' observations of our dependent variables are based on overlapping snow data.

We next analyze how the changing snow conditions in Austrian ski resorts affect firm-level employment. As discussed above, the firms in our sample face exogenous labor productivity risk since the snow conditions affect tourists' demand for accommodation and related services. We test whether the firms manage this risk by adjusting their employment when the snow conditions change during the season. If/once there is ample snow for skiing, the firms can safely assume that skiing will remain possible for some time. During the starting weeks of the skiing season, it is, however, typically hard to predict the snow conditions more than a few days ahead since reliable weather forecasts are only available over short horizons. In this situation, many firms take labor productivity risk when they commit to employing workers, promising them pay before they generate uncertain revenues.[59] It is this risk-taking that we are particularly interested in, but we start our analysis by testing more comprehensively whether the firms respond to variation in snow conditions observed before and during a skiing season.

Table 5 reports regressions explaining firm-level employment of workers in ski tourism using our measures of expected snow, snow risk, and snow "news", i.e., the difference between the snow-week dummy in a given week and its mean over the last five years. The dependent variable is employee days $ED_{i,t,T}$, defined in expression (2) above. We use this variable to measure firms' employment based on the employment spells that fall into the skiing season. Its mean variation across the skiing weeks is depicted by the dashed line in Figure 2. Our regressions test formally for effects of the snow variables defined in expressions (4) and (5) while allowing for fixed effects at the firm-year and week levels. The firm-year fixed effects control for determinants of firm-level

[59] As discussed in Section 3, the firms need to allow many of their workers some time to move before they can start working. As a consequence, they have to hire the workers well before the start of the skiing season. This is possible because the firms can trust that a potential late start of the skiing season is a temporary negative shock to labor productivity, rather than a persistent shock. See Guiso et al. (2005) for evidence that firms insure their workers against temporary productivity shocks.

employment that remain constant across the weeks of a given skiing season. This includes effects of firms' permanent employment, their facilities (e.g., spas which entertain tourists when there is not enough snow for skiing), and capital structures, but also effects of ski resort infrastructure, location, etc. The week fixed effects control for trends affecting all ski resorts, e.g., general demand fluctuations due to official holidays in Austria and neighboring countries.[60]

As discussed above, we focus on the starting and ending weeks of the skiing season, i.e., the weeks in which the snow conditions determine demand in ski resorts since the hotels in the resorts are not booked out. We actually distinguish between the two sets of weeks because negative snow shocks are likely to be temporary shocks during the starting weeks, but these shocks are likely to be permanent during the ending weeks. By running separate regressions for the two types of weeks, we also allow for different fixed effects. The estimates appear in the two panels of Table 5, with standard errors clustered at the ski-resort level.

All estimates show that firms' employment during the skiing season responds significantly positively to expected snow. With respect to snow risk, we find a significantly negative effect, but only during the starting weeks. The opposite picture emerges with respect to snow news. It appears that the firms respond to snow news by adjusting their employment, but only during the ending weeks of the skiing season. The lack of similar evidence with respect to the starting weeks is consistent with the idea that, during these weeks, snow shocks are temporary shocks to labor productivity, and that firms insure their workers against these shocks.[61] This idea goes back to Knight (1971) and corroborating

[60] For example, schools in Vienna are always closed during the first week of February so that families can go skiing for one week.

[61] This is true for both negative and positive shocks because both types of shocks cause only temporary changes in labor productivity before the hotels are booked out after Christmas (− the start of the high season).

evidence appears in the literature following Guiso et al. (2005). Our results confirm the findings of this literature based on a novel identification strategy.

More importantly, we add evidence regarding effects of risk. In this respect, our analysis yields novel evidence because we identify effects of risk *conditional on* the effects of "news". This conditioning is key if we are to interpret our results as evidence regarding models in which firms commit to quasi-fixed labor costs when they hire employees. In fact, our evidence shows that snow risk affects employment during the weeks in which snow news do not. In our main analysis, we will refine our analysis in order to obtain estimates that can be explicitly interpreted as evidence regarding labor productivity risk. For now, we can only interpret the estimates with respect to snow risk.

To assess the economic significance of the effect of snow risk, we use the standard deviation of snow risk within ski resort-years, reported in Table 1. Given this standard deviation of 20%, the coefficient of snow risk in Table 5 implies that a one-standard deviation increase in the risk reduces employment in ski tourism during the skiing season's starting weeks by about 3%.

Overall, the results in this section suggest that, while we consider a specific sample of firms exposed to a particularly quantifiable type of exogenous labor productivity risk, we actually focus on firms that behave like many other firms in terms of risk-sharing with their workers: It appears that the firms take the risk of temporary labor productivity shocks, but not that of more persistent shocks. This suggests that we should also obtain externally valid results when we analyze the firms' response to snow risk as a source of labor productivity risk affecting the firms to a degree determined by their (quasi-fixed) employment.

5.2 Bank equity and employment

5.2.1 OLS estimates

In this section, we present estimates regarding our main regressions, i.e., the regressions of the type stated in expression (1). We start by presenting ordinary least squares (OLS) estimates. Table 6 reports first tests of the hypothesis that bank equity affects the risk-taking of the firms in our sample with respect to the risk of temporary labor productivity shocks due to snow risk. For now, we focus on the starting weeks of the skiing season, i.e., the weeks during which the firms' employment appears to be quasi-fixed with respect to snow news. The regressions extend those in Table 5. They not only include our snow variables, but also their interactions with measures of the equity ratios of banks in the vicinity of the firms in our sample. We measure these equity ratios in terms of basis points because they are generally quite small, typically taking values between 5 and 10%.

The main coefficient of interest is that of the interaction of bank equity and snow risk. Our OLS estimates of this coefficient are first evidence regarding the effect of bank equity as a variable modulating the negative effect of snow risk on employment.[62] All estimates suggest that firms in areas with more bank equity take more risk by employing more workers. While employment decreases in snow risk, the coefficient of the interaction of snow risk and bank equity is significantly positive. We also find that employment is lower in resorts with less expected snow, and that this correlation appears to be weaker in areas where banks have more equity capital. Below, we however find that, this last effect is not robust. In our instrumental variables (IV) regressions, only the coefficient of the interaction of bank equity and snow risk remains statistically

[62] Alternatively, bank equity may simply proxy for the extent to which snow risk causes labor productivity risk. We address this issue by means of instrumental variables estimates. See Section 5.2.2.

significant. These regressions will allow us to more specifically interpret our estimates as causal evidence that bank equity affects firms' risk-taking with respect to exogenous labor productivity risk.

The evidence in Table 6 is robust with respect to changing our measures of bank equity in a number of ways. We start by measuring bank equity at the bank-level based on data about all banks, i.e., we use the variable defined in expression (6). Next, we only consider regional banks that are part of banking groups, using the measure of bank equity in expression (7). Both specifications result in rather similar estimates. Slightly larger estimates result from measuring bank equity at the level of banking groups, rather than at the bank-level. These estimates appear in the second part of Table 6. They are based on data about the many regional Austrian banks that are part of banking groups, cooperating in their lending activities and sharing internal equity capital markets, i.e., the savings banks and cooperative banks. By measuring bank equity at the group-level, we obtain measures that are exogenous because the groups operate throughout Austria, so that their business in any particular ski resort will only have a negligible effect on their aggregate equity capital.

The next-to-last column of Table 6 presents estimates in which we measure bank equity at the group-level for all banks that actually belong to banking groups. For the other banks, we continue to measure their equity capital at the bank level, at the risk that the resulting estimates are subject to endogeneity biases.[63] To avoid this risk, we also present estimates that result from only using the group-level measures of bank equity. These estimates appear in the last column of Table 6. They result from only using data about regional banks which are part of banking groups and measuring bank equity according to expression (8). The resulting measure will be used below in IV regressions, and the OLS estimates in the last column of Table 6 can be seen as the correspond-

[63] For further discussion, see the following section.

ing reduced-form estimates. We no longer observe a significant effect of the interaction of bank equity and expected snow, but again find that bank equity alleviates the negative effect of snow risk on employment. It thus appears that bank equity acts as a catalyst for the risk taking firms engage in when they commit to quasi-fixed employment. If we interpret the estimates of our OLS regressions in a causal way, they suggest that an additional basis point of bank equity reduces the negative effect of snow risk on employment by about 1%, i.e., the ratio of the coefficient of the interaction of snow risk and bank equity and the baseline coefficient of snow risk.[64] Estimates of this ratio appear in the bottom of Table 6.

We next test whether similar results can also be obtained based on the data about the ending weeks of the skiing season. During these weeks, the firms' employment does not appear to be quasi-fixed: The estimates in Table 5 show that the firms respond to snow "news" by adjusting their employment, and that we cannot find the significantly negative effect of snow risk on employment observed during the skiing season's starting weeks. These results suggest that, during the season's ending weeks, the firms' are not committing to a quasi-fixed level of employment associated with ski tourism. Instead, their workers appear to bear labor productivity risk associated with snow risk. If the firms are indeed not taking this risk, then they avoid the risk of liquidity shocks which would otherwise be caused by employees not being able to "earn their pay". As a consequence, the firms' employment should not depend on bank equity as a proxy for banks' ability to provide liquidity insurance to the firms.

Table 7 shows the results of a placebo test in which we use our data about the ending weeks of the skiing season in order to replicate the analysis behind the results reported in Table 6. Confirming the results in Table 5, we again find no significant main effect of snow risk on employment associated with

[64] In expression (1), this ratio is denoted as β_1/β_0.

ski tourism. The coefficients of snow risk are also much smaller than those in Table 6. The same is true for the coefficients of the interaction of snow risk and bank equity. In fact, only one of these coefficients has a statistically significant estimate. This estimate results from our bank-level measure of bank equity and may therefore be biased by endogeneity of bank equity.[65] If we instead use our group-level measures of bank equity, we find no statistically significant evidence that bank equity modulates the effect of snow risk on employment during the ending weeks of the skiing season. All in all, the placebo test is rather consistent with the idea that, during the season's ending weeks, snow risk induces a labor productivity risk (mostly) borne by workers in ski tourism.

Overall, our analysis so far highlights that the effect of risk on employment depends both on the extent to which employment is quasi-fixed, and on bank equity. The first effect shows that analyses measuring effects of risk on employment need to be based on prior tests regarding the risk-sharing between firms and their employees. To the best of our knowledge, our paper is the first to employ this research strategy. In the remainder of the paper, we will focus on the second result, i.e., the effect of bank equity.

5.2.2 IV estimates

In this section, we address the issue that we cannot directly observe the extent to which snow risk causes labor productivity risk in our sample of firms. In interpreting our previous estimates as evidence that bank equity affects firms' risk-taking with respect to labor productivity risk, we implicitly assume that it does not affect the extent to which this risk is caused by snow risk. This assumption cannot be tested without direct data about labor productivity.

[65] In our IV regressions, we in fact find direct evidence that bank equity is endogenous if measured at the bank level. The endogeneity problem notwithstanding, a positive coefficient of the interaction of snow risk and bank equity could also indicate that the ending and starting weeks of the skiing season are not that different in terms of the effect of snow risk on employment associated with ski tourism. Some of this employment may also be quasi-fixed during the season's ending weeks.

We can, however, rule out that we use variation in bank equity which may be correlated with variation across firms or ski resorts in the extent to which snow risk causes labor productivity risk. This allows us to measure the effect of bank equity on the extent to which labor productivity risk reduces firms' quasi-fixed employment.

This causal effect of bank equity is measured in Table 8 which presents our IV estimates. As discussed in Section 2, these estimates are based on institutional features of the Austrian banking sector, i.e. that many regional Austrian banks are part of banking groups, cooperating in their lending activities and sharing internal equity capital markets. We instrument the equity capital ratios of individual regional member banks of the various banking groups using the aggregate equity capital ratio of a bank's group. The instrument is defined in expression (8). To use this instrument, we must, however, focus on effects of the equity capital buffers of banks that are actually part of a banking group, i.e., the savings banks and cooperative banks.[66] The reduced form estimates appear in the last column of Table 6.

The IV estimates appear in the right-most column of Table 8. The two preceding columns present two first stage regressions, regarding the interactions of bank equity with expected snow and snow risk. The first column of estimates in Table 8 repeats the OLS estimates (which also appeared in the second column of estimates in Table 6). Throughout, we use the same large set of fixed effects as in Table 6 and again report clustered standard errors (at the village level). The fixed effects control for the effect of bank equity per se.

In the first-stage regressions, we obtain satisfactory results of the F-tests for the excluded instrument. Comparing the OLS and IV estimates shows that the puzzling negative coefficient of the interaction of expected snow and bank equity becomes statistically insignificant when we instrument this interaction

[66] There are two types of cooperative banks, i.e., the Volksbanken and the Raiffeisenbanken.

term. The coefficient's point estimate is closer to zero, with a wider confidence interval relative to the corresponding OLS estimates. We also obtain a substantially wider confidence interval for the coefficient of the interaction of snow risk and bank equity, but the IV point estimate of this coefficient is more negative than the OLS point estimate. As a consequence, this coefficient remains statistically significant. To assess the economic significance of the effect of bank equity, we again compare the coefficient of its interaction with snow risk to the coefficient of snow risk per se. The ratio of the two coefficients is denoted as β_1/β_0 in expression (1). In terms of this ratio, reported in the bottom of Table 8, the IV results are rather similar to the OLS results.

All in all, our estimates reveal that banks' equity capital buffers affect the risk-taking of firms in the banks' vicinity when they commit to employing workers on a quasi-fixed basis. The IV estimates allow for a more specific interpretation of the results as evidence concerning firms' risk-taking with respect to labor productivity risk induced by weather risk. They show that bank equity does not just proxy for variation across firms in the extent to which snow risk causes labor productivity risk. While this may be true, the IV estimates show that the effect of the latter risk on firms' employment depends on bank equity.

6 Further results

In this section, we extend our analysis to take into account further characteristics of local banking and labor markets. We test for cross-sectional variation in the effect of bank equity on the risk-taking of firms when they commit to quasi-fixed employment. If this effect exists because firms rely on banks as providers of liquidity insurance, then we should see stronger effects in markets where a lack of bank equity more strongly constrains the availability of this liquidity insurance because other constraints are less binding. Moreover, we should see stronger effects in labor markets where firms find it harder to respond to labor productivity shocks by adjusting their employment.

6.1 Variation across regional banking markets

In this section, we contrast regional banking markets that differ in terms of the number of banks, the banks' geographic diversification, and their liquidity. We hypothesize that, in markets with more banks or more diversified/more liquid banks, firms' access to bank-provided liquidity insurance depends more strongly on bank equity.

We test this hypothesis by extending our previous regressions in order to include triple interactions of snow risk, bank equity, and one of the three other variables mentioned above. Moreover, we check the robustness of the effect of bank equity in horse-race specifications in which we include the other variables in the same way in which bank equity appears in the regressions. The tests will appear in regressions based on our data about the starting weeks of the skiing season, i.e., the weeks during which the employment of the firms in our sample can be regarded as quasi-fixed.

Tables 9 - 11 report the results. In each table, the first column of estimates repeats the results of a previously reported regression based on the measure of bank equity that results from measuring bank equity at the level of banking groups except for banks that do not belong to a group. The second column shows regressions in which we just test whether another characteristic of banking markets affects our firms' risk-taking when they commit to quasi-fixed employment. We find that this risk-taking tends to increase in the number of banks in a region (Table 9), as well as in the extent of the banks' geographic diversification (Table 10). These results appear to be robust, as illustrated by the estimates based on the horse-race specifications reported in the third column of estimates in each table. The estimates also confirm the robustness of the effect of bank equity. In all tables, we observe similar coefficients of the interaction of snow risk and bank equity in the first column (baseline estimates) and the third column (horse-race estimates).

With respect to banks' liquidity creation capacity (LCC), we find no significant coefficient of its interaction with snow risk, but we can also confirm that the effect of bank equity is robust in a horse-race specification, reported in the third column of estimates in Table 11. Moreover, we observe an interesting effect of LCC when we include its triple interaction with snow risk and bank equity. The last column of estimates in Table 11 reports that the coefficient of the triple interaction is significantly positive. It appears that, in markets with higher LCC, bank equity more strongly alleviates the negative effect of snow risk on employment. This is consistent with the hypothesis that, in markets with higher LCC, bank equity more strongly constrains banks' provision of liquidity insurance to the firms in our sample, and, thus, the firms' capacity to take the risk of liquidity shortfalls due to labor productivity shocks.

Similar hypotheses explain the results we obtain when we use triple interaction terms based on the two other features of banking markets, i.e., the number of banks and banks' geographic diversification. The coefficients of these variables interactions with snow risk and bank equity are reported in the last column of estimates in Tables 9 and 10. Both coefficients are significantly positive, consistent with the hypothesis that, in markets with more or more diversified banks, bank equity more strongly constrains banks' provision of liquidity insurance to the firms in our sample because other constraints are less binding. This is also consistent with our previous findings that snow risk has a smaller negative effect on the employment of firms in markets with more or more diversified banks.

In summary, the results in Tables 9 - 11 are all consistent with our interpretation of the effect of bank equity on the way firms' quasi-fixed employment responds to snow risk as a source of labor productivity risk in our sample. The results suggest that bank equity affects firms' access to bank-provided liquidity insurance when they take the risk of liquidity shocks induced by labor productivity shocks. We find that a lack of bank equity more strongly constrains the availability of this liquidity insurance in markets in which other constraints are less binding because there are more or more diversified/more liquid banks.

6.2 Labor market tightness

Our results relate to employment being quasi-fixed at the beginning of the season. This is due to the hotel's need to fix the manpower before the first guest arrives at the start of the season and the impossibility to intermittently reduce and refill this manpower at will. As all hotels in the Alps start their skiing season around the same time, getting rid of dispensable workers in case of unexpectedly bad snow conditions is too risky for the hotel, because the employees – around 30 % of them foreign nationals – might be poached by other hotels. This should be even more so, the more tight local labor markets are. Notwithstanding the high share of foreign workers, local labour market tightness should increase the amount of quasi-fixed-ness of early-season employment.

In Table 12 we split our sample into two subgroups according to the labor market tightness of the county in which the firm operates. The labor market tightness is defined as $(1 - \text{unemployment rate}_{c(i),T})$ in county $c(i)$ and year T. We present results for the early season only. The average unemployment rate in the high LMT regions is 6.7%, but 12.8% in the low LMT region, which is a quite substantial variation.

Here, we see that in regions with high labor market tightness, hotel's employment reacts more negatively to ex-ante snow risk as hotels in regions with lower labor market tightness do. Moreover, this negative reaction to snow risk in high LMT regions is exacerbated if the local banks lack equity capital. This is consistent with the idea that bank equity affects firms' capacity to commit to quasi-fixed employment because employment should be more quasi-fixed in areas with tighter labor markets.

In contrast to all previous results, we see in the case of hotels in regions with low labor market tightness that firms do adapt their employment in the case of positive snow news – even in the early season. Low labor market tightness does not make insuring workers for temporary shocks necessary for the hotel: workers can be found in the market. These results suggest that our evidence is generally relevant for firms in industries and regions with tight labor markets.

7 Conclusion

We analyze the effect of risk on small-firm employment. The analysis is based on highly granular data about a sample of small firms exposed to weather risk as a particularly quantifiable risk affecting the productivity of the firms' employees. We find that the firms' employment is quasi-fixed with respect to snow risk as a cause of transitory shocks to labor productivity, but not with respect to more permanent shocks during the ending weeks of the skiing season. While the transitory shocks during the season's starting weeks have no direct effects, the firms' employment varies in the snow risk driving these shocks. We thus provide evidence that labor productivity risk affects quasi-fixed employment. The evidence is consistent with central assumptions in the macroeconomic models of Quadrini (2017) and Arellano et al. (2019). To the best of our knowledge, prior analyses of the effects of risk on employment were not explicitly focused on the quasi-fixed form of employment which appears in the models.

We also measure the effect of bank equity on the risk-taking that firms engage in when they employ workers on a quasi-fixed basis even though the productivity of the workers is subject to transitory shocks. Instrumental variables estimates show that firms take more labor productivity risk if the banks in the firms' vicinity hold more equity capital. To assess the economic significance of this effect, we measure its size relative to the baseline effect of snow risk on firms' (quasi-fixed) employment. It thus turns out that our analysis identifies a real effect of bank equity which is not only statistically but also economically significant. We thus add to the literature on employment effects of changes in risk that occur against the backdrop of financial market imperfections.

Our analysis is motivated by the idea that firms need insurance against liquidity shocks in order to provide workers with stable employment and pay even though they generate uncertain revenues. The empirical findings of this paper suggest that small firms depend on liquidity insurance provided by local banks. If these banks lack equity capital, the firms' employment responds more strongly to changes in the risk of liquidity shocks hitting the firms when their workers are temporarily unable to "earn their pay". This is consistent with the idea that bank liquidity creation gets impaired when banks lack equity capital.[67] It seems that the firms in our sample cannot easily switch to other ways of obtaining liquidity, e.g., by means of positions in weather derivatives. In this respect, they may be similar to other small firms. As a risk of rather verifiable shocks, weather risk should be particularly suited for risk-sharing between small firms and their banks. By offering this risk-sharing to many small firms in their vicinity, banks should be able to realize economies of scale that would remain unrealized if the firms sought to individually insure themselves against weather risk.

The results of our analysis highlight that bank equity capital regulation is relevant for economic adaptation to climate change. We argue that bank equity affects banks' performance as risk-sharing partners of firms in the real econ-

[67] See Berger and Bouwman (2009) for a review of the literature regarding bank liquidity creation.

omy. While we stress risk-sharing with respect to the risk of weather-induced liquidity shocks, weather risk should also cause other financial risks. We think that it will be key to understand the real effects of these risks, and we hope that this paper motivates further research by documenting an important real effect of bank equity.

References

Acharya, V., I. Hasan, and A. Saunders (2006). Should banks be diversified? evidence from individual bank loan portfolios. *The Journal of Business 79*(3), 1355–1412.

Agarwal, S. and R. Hauswald (2010, 06). Distance and private information in lending. *Review of Financial Studies 23*, 2757–2788.

Akhigbe, A. and A. Whyte (2003, 01). Changes in market assessments of bank risk following the riegle-neal act of 1994. *Journal of Banking and Finance 27*, 87–102.

Alessandri, P. and H. Mumtaz (2017). Financial conditions and density forecasts for us output and inflation. *Review of Economic Dynamics 24*, 66–78.

Alfaro, I., N. Bloom, and X. Lin (2018, May). The finance uncertainty multiplier. Working Paper 24571, National Bureau of Economic Research.

Alnahedh, S., S. Bhagat, and I. Obreja (2019). Employment, corporate investment, and cash-flow risk. *Journal of Financial and Quantitative Analysis 54*(4), 1855–1898.

Arellano, C., Y. Bai, and P. J. Kehoe (2019). Financial frictions and fluctuations in volatility. *Journal of Political Economy 127*(5), 2049–2103.

Banerjee, R., L. Gambacorta, and E. Sette (2017). The real effects of relationship lending. *Bank of Italy Temi di Discussione (Working Paper) No 1133.*

Beck, A., J. Hiebl, E. Koch, R. Potzmann, and W. Schöner (2009). Institutionelle und regulatorische Fragestellungen der Bereitstellung von Wetterdaten. *Graz: Economics of Weather and Climate Risks Working Paper Series* (10).

Beck, T., H. Degryse, R. De Haas, and N. Van Horen (2018). When arm's length is too far: Relationship banking over the credit cycle. *Journal of Financial Economics 127*(1), 174–196.

Benmelech, E., N. Bergman, and A. Seru (2015, 06). Financing labor. *SSRN Electronic Journal.*

Bentolila, S., M. Jansen, and G. Jimenez (2017, 08). When Credit Dries Up: Job Losses in the Great Recession. *Journal of the European Economic Association 16*(3), 650–695.

Berger, A., A. Demirguc-Kunt, R. Levine, and J. Haubrich (2004, 02). Bank concentration and competition: An evolution in the making. *Proceedings 36*, 433–451.

Berger, A. N. and C. H. Bouwman (2009). Bank liquidity creation. *The Review of Financial Studies 22*(9), 3779–3837.

Berger, P., M. Minnis, and A. Sutherland (2017). Commercial lending concentration and bank expertise: Evidence from borrower financial statements. *Accounting.*

Bharath, S., S. Dahiya, A. Saunders, and A. Srinivasan (2011, 10). Lending relationships and loan contract terms. *Review of Financial Studies 24*, 1141–1203.

Black, S. and P. Strahan (2002, 02). Entrepreneurship and bank credit availability. *Journal of Finance 57*, 2807–2833.

Bolton, P., X. Freixas, L. Gambacorta, and P. E. Mistrulli (2016). Relationship and transaction lending in a crisis. *The Review of Financial Studies 29*(10), 2643–2676.

Boot, A. and A. Thakor (2000, 02). Can relationship banking survive competition? *Journal of Finance 55*, 679–713.

Boot, A. W. A. (2000). Relationship banking: What do we know? *Journal of Financial Intermediation 9.1*, 7–25.

Bouwman, C. H. S. (2019). Creation and regulation of bank liquidity. In A. N. Berger, P. Molyneux, and J. O. S. Wilson (Eds.), *The Oxford Handbook of Banking (3rd edn)*, Chapter 7. Oxford University Press.

Broecker, T. (1990). Credit-worthiness tests and interbank competition. *Econometrica 58*(2), 429–52.

Bülbül, D., R. H. Schmidt, and U. Schüwer (2014). Savings banks and cooperative banks in Europe. *Bezpieczny Bank 2(55)*, 38–49.

Caggese, A. and V. Cuñat (2008). Financing constraints and fixed-term employment contracts. *The Economic Journal 118*(533), 2013–2046.

Campiglio, E., Y. Dafermos, P. Monnin, J. Ryan-Collins, G. Schotten, and M. Tanaka (2018). Climate change challenges for central banks and financial regulators. *Nature Climate Change 8*(6), 462.

Cardoso, A. R. and M. Portela (2009). Micro foundations for wage flexibility: wage insurance at the firm level. *Scandinavian Journal of Economics 111*(1), 29–50.

Carletti, E. (2004, January). The structure of bank relationships, endogenous monitoring, and loan rates. *Journal of Financial Intermediation 13*(1), 58–86.

Carletti, E., V. Cerasi, and S. Daltung (2007, July). Multiple-bank lending: Diversification and free-riding in monitoring. *Journal of Financial Intermediation 16*(3), 425–451.

Cerqueiro, G., H. Degryse, and S. Ongena (2011). Rules versus discretion in loan rate setting. *Journal of Financial Intermediation 20*(4), 503–529.

Chodorow-Reich, G. (2013). The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis. *The Quarterly Journal of Economics 129*(1), 1–59.

Chong, B. S. (1991, February). The Effects of Interstate Banking on Commercial Banks' Risk and Profitability. *The Review of Economics and Statistics 73*(1), 78–84.

Christiano, L. J., R. Motto, and M. Rostagno (2014). Risk shocks. *American Economic Review 104*(1), 27–65.

Cole, R., L. Goldberg, and L. White (2004, 06). Cookie cutter vs. character: The micro structure of small business lending by large and small banks. *Journal of Financial and Quantitative Analysis 39*, 227–251.

Degryse, H., M. Kim, and S. Ongena (2009). *Microeconometrics of banking: methods, applications, and results.* Oxford University Press, USA.

Degryse, H. and S. Ongena (2005). Distance, lending relationships, and competition. *The Journal of Finance 60*(1), 231–266.

Degryse, H. and S. Ongena (2007, July). The impact of competition on bank orientation. *Journal of Financial Intermediation 16*(3), 399–424.

Dell, M., B. F. Jones, and B. A. Olken (2014). What do we learn from the weather? the new climate-economy literature. *Journal of Economic Literature 52*(3), 740–98.

Dell'ariccia, G. and R. Marquez (2004). Information and bank credit allocation. *Journal of Financial Economics 72*(1), 185–214.

DeLong, G. L. (2001). Stockholder gains from focusing versus diversifying bank mergers. *Journal of Financial Economics 59*(2), 221–252.

Demsetz, R. S. and P. E. Strahan (1997). Diversification, size, and risk at bank holding companies. *Journal of Money, Credit and Banking 29*(3), 300–313.

Deng, S. and E. Elyasiani (2008, 09). Geographic diversification, bank holding company value, and risk. *Journal of Money, Credit and Banking 40*, 1217–1238.

Dinc, S. (2000, 07). Bank reputation, bank commitment, and the effects of competition in credit markets. *Review of Financial Studies 13*, 781–812.

Doerflinger, C., A. Doerflinger, K. Gavac, and B. Vogl (2013). *Familienunternehmen in Oesterreich.* KMU Forschung Austria.

Drucker, S. and M. Puri (2007, 12). Banks in capital markets. *Handbook of Empirical Corporate Finance SET 2*, 189–232.

DSGV (2012). Inside the savings banks finance group.

ECB (2017). Report on financial structures.

Ellul, A., M. Pagano, and F. Schivardi (2018). Employment and wage insurance within firms: Worldwide evidence. *The Review of Financial Studies 31*(4), 1298–1340.

Elsas, R. (2005). Empirical determinants of relationship lending. *Journal of Financial Intermediation 14*(1), 32–57.

Elsas, R. and J. P. Krahnen (1998). Is relationship lending special? evidence from credit-file data in germany. *Journal of Banking and Finance 22*(10-11), 1283–1316.

Eurostat (2006). Panorama on tourism.

Freixas, X. and J.-C. Rochet (1997, 01). *The Microeconomics of Banking.*

Gilchrist, S., J. W. Sim, and E. Zakrajsek (2014, April). Uncertainty, financial frictions, and investment dynamics. Working Paper 20038, National Bureau of Economic Research.

Giroud, X., H. M. Mueller, A. Stomper, and A. Westerkamp (2011). Snow and Leverage. *The Review of Financial Studies 25*(3), 680–710.

Goetz, M. (2012). Bank diversification, market structure and bank risk taking: theory and evidence from U.S. commercial banks. Technical report.

Goetz, M. R. (2018). Competition and bank stability. *Journal of Financial Intermediation 35*(PA), 57–69.

Guertzgen, N. (2014). Wage insurance within German firms: Do institutions matter? *Journal of the Royal Statistical Society: Series A (Statistics in Society) 177*(2), 345–369.

Guiso, L., E. Detragiache, and P. Garella (2000, 02). Multiple versus single banking relationships: Theory and evidence. *Journal of Finance 55*, 1133–1161.

Guiso, L., L. Pistaferri, and F. Schivardi (2005). Insurance within the firm. *Journal of Political Economy 113*(5), 1054–1087.

Hamermesh, D. (1989). Labor demand and the structure of adjustment costs. *American Economic Review 79*(4), 674–89.

Hauswald, R. and R. Marquez (2006). Competition and strategic information acquisition in credit markets. *The Review of Financial Studies 19*(3), 967–1000.

HLEG, E. (2018). Final report 2018 by the high-level expert group on sustainable finance. *Retrieved from European Commission website: https://ec. europa. eu/info/publications/180131-sustainable-finance-report_en.*

Holmström, B. and J. Tirole (1998). Private and public supply of liquidity. *Journal of Political Economy 106*(1), 1–40.

Kátay, G. (2016). Do firms provide wage insurance against shocks? *Scandinavian Journal of Economics 118.1*, 105–128.

Knight, F. H. (1971). Risk, uncertainty and profit, 1921. *Library of Economics and Liberty.*

Krogstrup, S. and W. Oman (2019). Macroeconomic and financial policies for climate change mitigation: A review of the literature.

Levine, R., C. Lin, and W. Xie (2020). Geographic diversification and banks' funding costs. *Management Science.* Forthcoming.

Lhuissier, S., F. Tripier, et al. (2016). Do uncertainty shocks always matter for business cycles? *Centre d Etudes Prospectives et d Informations Internationales research center*.

Liberti, J. and A. Mian (2009, 09). Estimating the effect of hierarchies on information use. *Review of Financial Studies 22*, 4057–4090.

Liberti, J. M. and M. A. Petersen (2019). Information: Hard and soft. *Review of Corporate Finance Studies 8*(1), 1–41.

Marco, F. D. and S. Petriconi (2019). Bank Competition and Information Production. Technical report.

Marquez, R. (2002). Competition, adverse selection, and information dispersion in the banking industry. *Review of Financial Studies 15*(3), 901–926.

Nguyen, H.-L. Q. (2019). Are credit markets still local? evidence from bank branch closings. *American Economic Journal: Applied Economics 11*(1), 1–32.

Nigro, P., R. DeYoung, and D. Glennon (2008, 02). Borrower-lender distance, credit scoring, and loan performance: Evidence from informational-opaque small business borrowers. *Journal of Financial Intermediation 17*, 113–143.

Ogura, Y. (2012). Lending competition and credit availability for new firms: Empirical study with the price cost margin in regional loan markets. *Journal of Banking and Finance 36*(6), 1822–1838.

Oi, W. (1962). Labor as a quasi-fixed factor. *Journal of Political Economy 70*.

Pagano, M. (2019). Risk sharing within the firm: a primer. Centre for Studies in Economics and Finance (CSEF), University of Naples, Working Paper 553.

Petersen, M. A. and R. Rajan (1995). The effect of credit market competition on lending relationships. *The Quarterly Journal of Economics 110*(2), 407–443.

Petersen, M. A. and R. G. Rajan (2002). Does distance still matter? the information revolution in small business lending. *The Journal of Finance 57*(6), 2533–2570.

Presbitero, A. and A. Zazzaro (2011). Competition and relationship lending: Friends or foes? *Journal of Financial Intermediation 20*(3), 387–413.

Quadrini, V. (2017). Bank liabilities channel. *Journal of Monetary Economics 89*, 25–44.

Rice, T. and P. E. Strahan (2010). Does credit competition affect smallâĂŘfirm finance? *Journal of Finance 65*(3), 861–889.

Schwert, M. (2018). Bank capital and lending relationships. *The Journal of Finance 73.2*, 787–830.

Skrastins, J. and V. Vig (2018, 01). How organizational hierarchy affects information production. *SSRN Electronic Journal*.

Srinivasan, A. (2014, 01). Long run relationships in banking. *Foundations and TrendsÂő in Finance 8*, 55–143.

Statistik Austria (2018). Bestandsstatistik Tourismus. STATcube - Statistische Datenbank von STATISTIK AUSTRIA. [accessed 2018-Sep-4].

Stein, J. C. (2002). Information production and capital allocation: Decentralized versus hierarchical firms. *The Journal of Finance 57*(5), 1891–1921.

Steuerberatung, P. (2018). Was muss bei Hotellerie Saisonarbeit beachtet werden. online. last assessed Nov 10, 2019.

Stock, J. H. and M. W. Watson (2012). Generalized shrinkage methods for forecasting using many predictors. *Journal of Business & Economic Statistics 30*(4), 481–493.

Strahan, P. (2008, 12). *Bank Structure and Lending: What We Do and Do Not Know*, pp. 107–131.

Thomä, J. and A. Hilke (2018). The green supporting factor-quantifying the impact on european banks and green finance.

Tirole, J. (2006). *The Theory of Corporate Finance*. Princeton University Press, USA.

Töglhofer, C., F. Eigner, and F. Prettenthaler (2011). Impacts of snow conditions on tourism demand in Austrian ski areas. *Climate Research 46*(1), 1–14.

Winton, A. (1999, September). Don't Put All Your Eggs in One Basket? Diversification and Specialization in Lending. Center for Financial Institutions Working Papers 00-16, Wharton School Center for Financial Institutions, University of Pennsylvania.

WKO (2016). *Tourismus und Freizeitwirtschaft in Zahlen - Österreichische und internationale Tourismus- und Wirtschaftsdaten.* Wirtschaftskammer

Österreich. Österreich, Wirtschaftskammer and und Freizeitwirtschaft, Bundessparte Tourismus.

Yafeh, Y. and O. Yosha (2002, 01). Industrial organization of financial systems and strategic use of relationship banking. *European Finance Review 5*.

Figures and Tables

Figure 1

This figure plots an average firm's total employment (solid line) and employment in ski tourism (dashed line). We measure employment in terms of person-days. We plot the variation in these averages over the weeks of the skiing season, i.e., between week 47 and week 15 of the subsequent year. The vertical red lines indicate the starting weeks and the ending weeks of the skiing season.

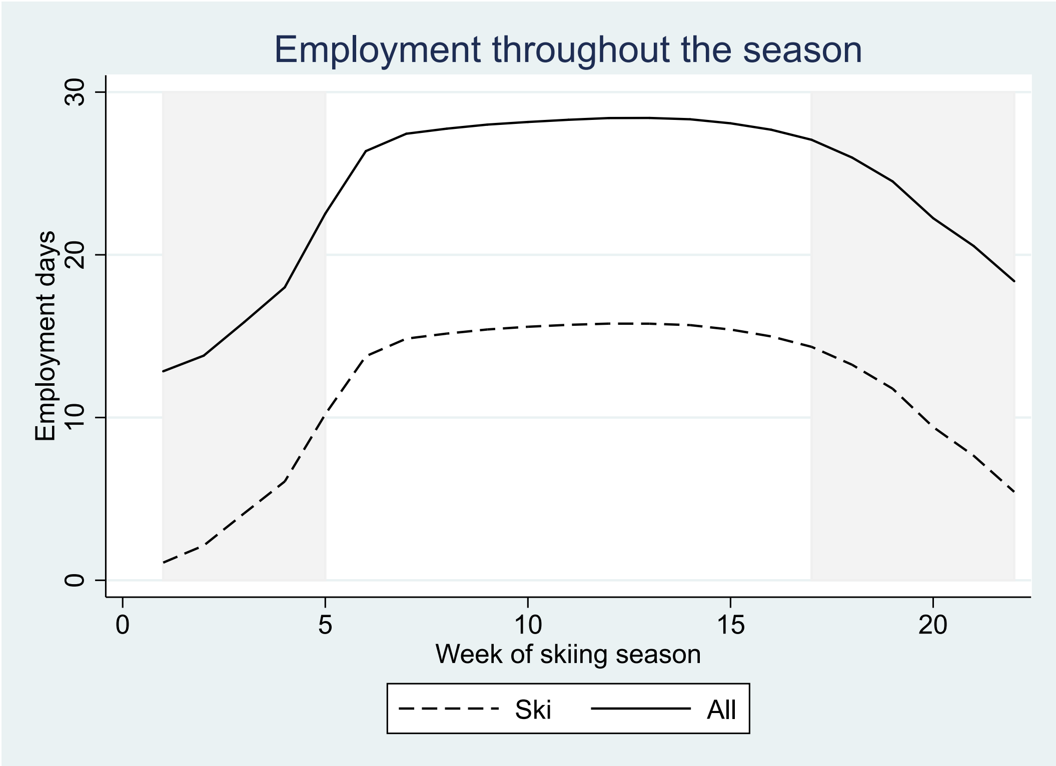

Table 1: Summary statistics: Snow conditions

This table reports summary statistics regarding the snow conditions in Austrian ski resorts during the years 1998-2006. We split the variation in the snow variables into variation between and within resort-years. The within component measures variation across the weeks of a winter season in a given ski resort. Snow days are defined as the number of days in a week for which the ski resort's average snow coverage exceeds 15 centimeters. Weeks in which the majority of days are snow days are considered snow weeks. Expected snow (Snow risk) is defined as the backward-looking 5 year average (standard deviation) of snow week in a given resort and week.

Variable	Category	Mean	SD	Min	Max	Obs
Winter season						
Snow days	overall	4.189	3.257	0	7	77490
	between		2.192			3690
	within		2.41			21
Snow week	overall	.594	.491	0	1	77490
	between		.317			3690
	within		.375			21
Average snow	overall	.556	.338	0	1	77490
	between		.249			3690
	within		.229			21
Snow risk	overall	.328	.241	0	.548	77490
	between		.136			3690
	within		.199			21
Starting weeks						
Snow days	overall	2.168	2.967	0	7	14760
	between		2.56			3690
	within		1.5			4
Snow week	overall	.3	.458	0	1	14760
	between		.382			3690
	within		.254			4
Average snow	overall	.288	.263	0	1	14760
	between		.217			3690
	within		.149			4
Snow risk	overall	.337	.237	0	.548	14760
	between		.178			3690
	within		.156			4
Ending weeks						
Snow days	overall	3.795	3.297	0	7	18450
	between		2.82			3690
	within		1.708			5
Snow week	overall	.541	.498	0	1	18450
	between		.412			3690
	within		.28			5
Average snow	overall	.5	.34	0	1	18450
	between		.31			3690
	within		.139			5
Snow risk	overall	.332	.242	0	.548	18450
	between		.193			3690
	within		.145			5

Figure 2

This figure plots variation in snow conditions during the skiing season. The solid line depicts the average of the snow week dummy over all ski resorts and all years. The dashed line plots the standard deviation of this ski week indicator during the sample period. The vertical red lines indicate the starting weeks and the ending weeks of the skiing season.

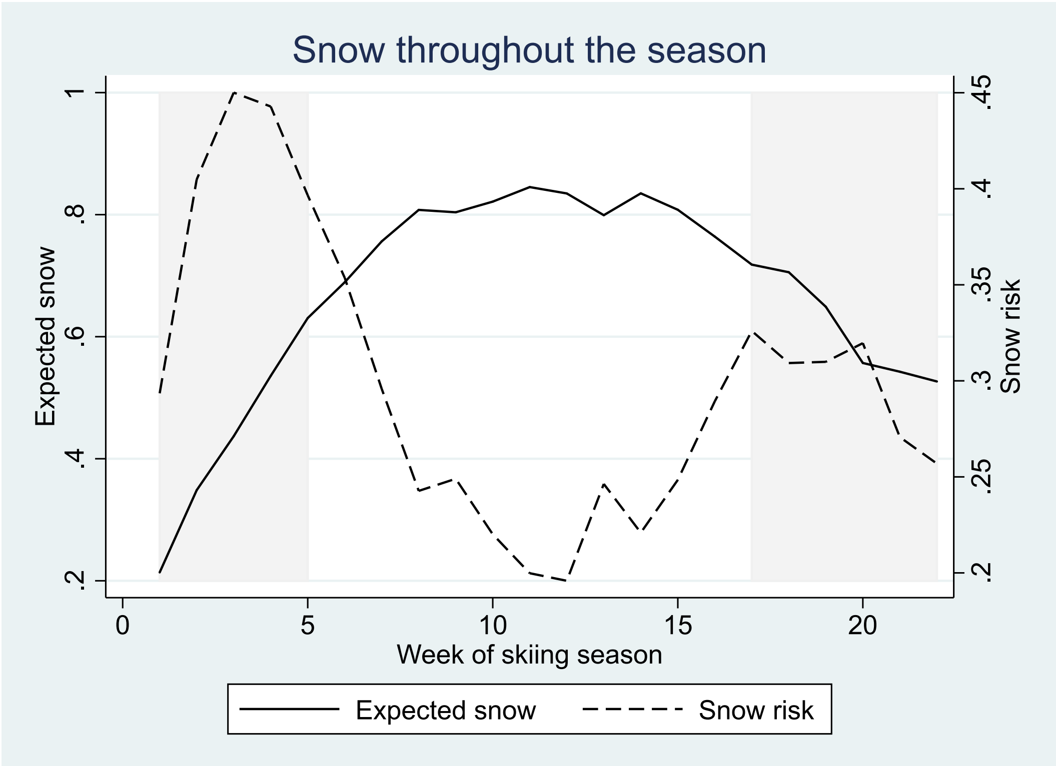

Figure 3

This figure illustrates the matching of snow data to firms, given the firms' municipality keys. We first collect the coordinates of all ski lifts within a radius of 10 km for each municipality's center. Next, we determine the closest data grid point to the center of each ski lift. Coordinates of ski lifts were retrieved from OpenStreetMap, the 1×1 km grid data on snow depth was provided by the Austrian Meteorological Office.

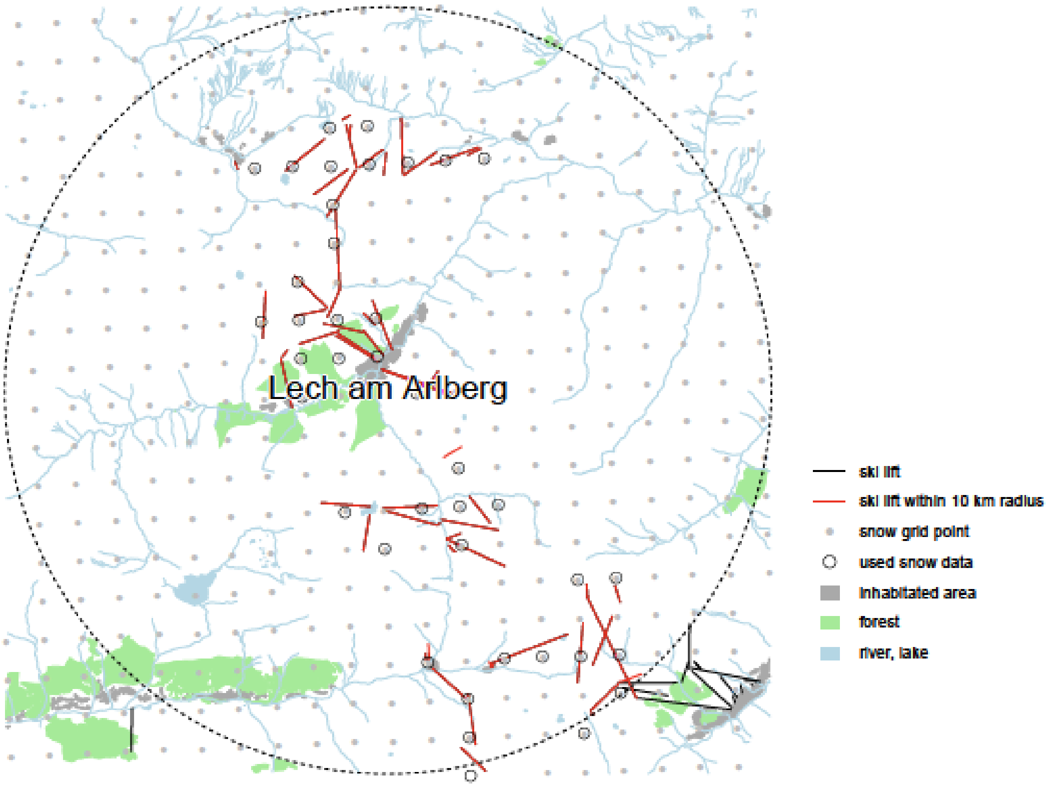

Table 2: Long run trends in snow conditions

This table reports regressions measuring long-run trends in our measures of expected snow and snow risk in Austrian ski resorts during the weeks of the skiing seasons 1983-2007. The dependent variables are defined in expression (4). We measure linear time trends and allow for the trends to differ across a number of dimensions. *Altitude* is a ski resort's altitude, and *High* is a dummy variable indicating ski resorts at above-median altitude. *Start* (*End*) are dummy variables indicating the starting (ending) weeks of the skiing season. In parentheses, we report standard errors clustered at the ski-resort level. *,**,*** indicate statistical significance at the 10%, 5% and 1% levels respectively.

	Expected Snow				Snow Risk			
$Year$	-0.00538***	-0.00591***	-0.00543***	-0.00605***	0.00271***	0.00209***	0.00402***	0.00390***
	(0.000172)	(0.000236)	(0.000184)	(0.000259)	(0.000175)	(0.000247)	(0.000216)	(0.000302)
$Year \times Altitude$	0.000938***		0.000962***		0.000332*		-0.000278	
	(0.000161)		(0.000173)		(0.000172)		(0.000197)	
$Year \times High$		0.00147***		0.00166***		0.00137***		0.000107
		(0.000335)		(0.000355)		(0.000336)		(0.000408)
$Year \times Start$			0.00640***	0.00599***			-0.00415***	-0.00494***
			(0.000241)	(0.000332)			(0.000277)	(0.000382)
$Year \times End$			-0.00491***	-0.00420***			-0.00219***	-0.00364***
			(0.000239)	(0.000308)			(0.000278)	(0.000382)
$Year \times Altitude \times Start$			0.000323				0.000866***	
			(0.000247)				(0.000266)	
$Year \times Altitude \times End$			-0.000361				0.00187***	
			(0.000245)				(0.000224)	
$Year \times High \times Start$				0.000960**				0.00197***
				(0.000474)				(0.000534)
$Year \times High \times End$				-0.00157***				0.00373***
				(0.000482)				(0.000530)
N	473550	473550	473550	473550	473550	473550	473550	473550
R^2	0.051	0.051	0.077	0.077	0.012	0.013	0.017	0.017
Resort-Week FE	YES	YES	YES	YES	YES	YES	YES	YES
Clustered SEs	Resort	Resort	Resort	Resort	Resort	Resort	Resort	Resort

Table 3: Summary statistics: Employment

This table reports summary statistics regarding the employment of firms in Austrian ski resorts during the years 1998-2006. We split the variation in our measures of employment into variation between and within firm-years. The within component measures variation across the weeks of a winter season in a given firm. The number of employees is defined as the sum of distinct employees of a hotel in a given week. Employment days is defined as the total number of days these workers are employed during a hotel-week. We report summary statistics for these variables based on all employees and based on firms' temporary employees during the skiing season.

Variable	Category	Mean	SD	min	max	Obs
			Winter season			
Employment days	overall	24.907	57.514	0	2853	1777902
	between		55.291			84662
	within		15.838			21
Employment days (temporary)	overall	12.309	35.24	0	1135	1777902
	between		32.508			84662
	within		13.603			21
			Starting weeks			
Employment days	overall	15.426	46.598	0	2256	338648
	between		45.585			84662
	within		9.665			4
Employment days (temporary)	overall	3.643	19.481	0	849	338648
	between		17.208			84662
	within		9.131			4
			Ending weeks			
Employment days	overall	24.274	56.147	0	2195	423310
	between		55.607			84662
	within		7.769			5
Employment days (temporary)	overall	11.485	33.816	0	987	423310
	between		32.986			84662
	within		7.444			5

Table 4: Summary statistics: Bank characteristics

This table reports summary statistics regarding variables describing the local banks in Austrian ski resort villages. We report the average equity ratio of banks operating in a 20 kilometer radius around the ski resorts, both for all banks (*all*) and for the subset of regional banks (*reg*). In each case, we report separate statistics based on bank-level balance sheet data and on balance sheet data aggregated at the level of Austria's banking groups (*grp*), e.g., the group of savings banks. The number of banks is defined as the number of distinct banking groups in a 20 kilometer radius around a ski resort. Branch diversification measures the degree of geographic expansion of the branch network of the "average bank" in a 20 kilometer radius around a ski resort. For formal definitions of the variables, see Section 4.1.

Variable	Mean	SD	Min	Max	Obs
Bank Equity^{all}	.082	.013	.054	.135	3654
Bank Equity^{grp,all}	.079	.008	.067	.1	3654
Bank Equity^{reg}	.08	.012	.054	.134	3654
Bank Equity^{grp,reg}	.08	.008	.067	.1	3654
Distinct banks^{grp}	5.753	2.193	2	11	3654
Branch Diversification	2008.702	1701.47	34.903	15408.6	3654

Table 5: Snow conditions and employment

This table reports results for regressions explaining the weekly employment days of firms in Austrian ski tourism during the years 1998-2006. The dependent variable is defined in expression (2). We use explanatory variables based on information about snow conditions known before the start of a season, and variables describing within-season variation in the snow conditions. The former variables are based on data about the last five skiing seasons and measure the expected snow conditions and snow risk in a ski resort-week. See expression (4) for formal definitions. $Snow_t$ denotes a dummy variable indicating whether there was enough snow for skiing during a resort-week. We report separate estimates based on data about the starting and ending weeks of the skiing season. In parentheses, we report standard errors clustered at the ski-resort level. *,**,*** indicate statistical significance at the 10%, 5% and 1% levels respectively.

	Log(employment days)					
	Starting weeks			Ending weeks		
Ex-ante						
Exp. snow_t	0.276***	0.277***	0.278***	0.336***	0.338***	0.339***
	(0.0524)	(0.0524)	(0.0525)	(0.0448)	(0.0451)	(0.0451)
Snow risk_t	-0.137***	-0.141***	-0.143***	-0.0246	-0.0225	-0.0216
	(0.0316)	(0.0319)	(0.0319)	(0.0303)	(0.0304)	(0.0304)
Within-season						
$\text{Snow}_t - \text{Exp. snow}_t$	0.0323	0.0284	0.0292	0.0608***	0.0554***	0.0590***
	(0.0199)	(0.0200)	(0.0191)	(0.0214)	(0.0202)	(0.0195)
$\text{Snow}_{t-1} - \text{Exp. snow}_{t-1}$		0.0182	0.0172		0.0240	0.0193
		(0.0185)	(0.0160)		(0.0155)	(0.0131)
$\text{Snow}_{t-2} - \text{Exp. snow}_{t-2}$			0.00429			0.0134
			(0.0211)			(0.0149)
N	325096	325096	325096	406370	406370	406370
R^2	0.167	0.167	0.167	0.186	0.186	0.186
Firm-Season FE	YES	YES	YES	YES	YES	YES
Week FE	YES	YES	YES	YES	YES	YES

Table 6: Snow conditions and employment: Effects of banks' equity ratios

This table reports results for regressions explaining the weekly employment days of firms in Austrian ski tourism during the years 1998-2006. We focus on the starting weeks of the skiing season. The dependent variable is defined in expression (2). We use explanatory variables measuring the expected snow and snow risk in a resort-week, based on data about the last five skiing seasons. See expression (4) for formal definitions. Bank Equity^{all} (Bank Equity^{reg}) is defined as the average equity ratio of all (regional) banks located in a 20 kilometer radius around a ski resort. In the first three columns, we measure banks' equity ratios using individual banks' balance sheets. In the last three columns, we use equity ratios aggregated at the level of banking groups, e.g., the group of savings banks. All equity ratio variables are de-meaned and defined in terms of basis points. In parentheses, we report standard errors clustered at the ski-resort level. *,**,*** indicate statistical significance at the 10%, 5% and 1% levels respectively. The ratio β_1/β_0 equals the coefficient of the interaction of snow risk and bank equity divided by the baseline coefficient of snow risk. Below our estimates regarding this ratio, we report the p-value of tests that it equals zero.

	Log(employment days)					
	Bank level			Group level		
Exp. snow$_t$	0.246***	0.221***	0.234***	0.246***	0.220***	0.239***
	(0.0486)	(0.0480)	(0.0480)	(0.0486)	(0.0459)	(0.0470)
Snow risk$_t$	-0.137***	-0.143***	-0.147***	-0.137***	-0.130***	-0.129***
	(0.0316)	(0.0326)	(0.0318)	(0.0316)	(0.0306)	(0.0309)
All banks						
Bank Equity^{all} × Exp. snow$_t$		-0.00138***			-0.00134**	
		(0.000327)			(0.000645)	
Bank Equity^{all} × Snow risk$_t$		0.000716***			0.000988***	
		(0.000256)			(0.000358)	
Regional banks						
Bank Equity^{reg} × Exp. snow$_t$			-0.00122***			-0.000437
			(0.000333)			(0.000654)
Bank Equity^{reg} × Snow risk$_t$			0.000702***			0.000796**
			(0.000251)			(0.000362)
N	325096	325096	325096	325096	325096	325096
R^2	0.167	0.168	0.168	0.167	0.167	0.167
Firm-Season FE	YES	YES	YES	YES	YES	YES
Week FE	YES	YES	YES	YES	YES	YES
β_1/β_0		-0.01	-0.00		-0.01	-0.01
P-Value		0.03	0.03		0.01	0.05

Table 7: Placebo test

This table reports results for regressions explaining the weekly employment days of firms in Austrian ski tourism during the years 1998-2006. We focus on the ending weeks of the skiing season. The dependent variable is defined in expression (2). We use explanatory variables measuring the expected snow and snow risk in a resort-week, based on data about the last five skiing seasons. See expression (4) for formal definitions. Bank Equity^{all} (Bank Equity^{reg}) is defined as the average equity ratio of all (regional) banks located in a 20 kilometer radius around a ski resort. In the first three columns, we measure banks' equity ratios using individual banks' balance sheets. In the last three columns, we use equity ratios aggregated at the level of banking groups, e.g., the group of savings banks. All equity ratio variables are de-meaned and defined in terms of basis points. In parentheses, we report standard errors clustered at the ski-resort level. *,**,*** indicate statistical significance at the 10%, 5% and 1% levels respectively. The ratio β_1/β_0 equals the coefficient of the interaction of snow risk and bank equity divided by the baseline coefficient of snow risk. Below our estimates regarding this ratio, we report the p-value of tests that it equals zero.

	Log(employment days)					
	Bank level			Group level		
Exp. snow$_t$	0.283***	0.261***	0.278***	0.283***	0.268***	0.260***
	(0.0404)	(0.0371)	(0.0393)	(0.0404)	(0.0380)	(0.0373)
Snow risk$_t$	-0.0143	-0.0372	-0.0145	-0.0143	-0.0196	-0.0278
	(0.0296)	(0.0267)	(0.0288)	(0.0296)	(0.0267)	(0.0261)
All banks						
Bank Equity^{all} × Exp. snow$_t$		0.000905***			0.000794*	
		(0.000265)			(0.000434)	
Bank Equity^{all} × Snow risk$_t$		0.000462**			-0.0000366	
		(0.000209)			(0.000319)	
Regional banks						
Bank Equity^{reg} × Exp. snow$_t$			0.000689***			0.000964**
			(0.000258)			(0.000421)
Bank Equity^{reg} × Snow risk$_t$			-0.000107			0.000122
			(0.000217)			(0.000312)
N	406370	406370	406370	406370	406370	406370
R^2	0.185	0.186	0.185	0.185	0.185	0.185
Firm-Season FE	YES	YES	YES	YES	YES	YES
Week FE	YES	YES	YES	YES	YES	YES
β_1/β_0		-0.01	0.01		0.00	-0.00
P-Value		0.25	0.73		0.91	0.71

Table 8: Instrumental variables estimates

This table reports results for instrumental variables (IV) regressions explaining the weekly employment days (ED) of firms in Austrian ski tourism during the years 1998-2006. We focus on the starting weeks of the skiing season. The dependent variable is defined in expression (2). We use explanatory variables measuring the expected snow and snow risk in a resort-week, based on data about the last five skiing seasons. See expression (4) for formal definitions. Bank Equity^{reg} is defined as the average equity ratio of all regionally active banks located in a 20 kilometer radius around a ski resort. These banks belong to banking groups, e.g., the group of savings banks. We use the aggregate equity ratio of a bank's group as an instrument, denoted as Bank Equity^{grp,reg}. All equity ratio variables are de-meaned and defined in terms of basis points. In parentheses, we report standard errors clustered at the ski-resort level. *,**,*** indicate statistical significance at the 10%, 5% and 1% levels respectively. The ratio β_1/β_0 equals the coefficient of the interaction of snow risk and bank equity divided by the baseline coefficient of snow risk. Below our estimates regarding this ratio, we report the p-value of tests that it equals zero.

	OLS	1st stage results		2nd stage
	Log(ED)	Bank Equity^{reg} × Exp. snow$_t$	Bank Equity^{reg} × Snow risk$_t$	Log(ED)
Exp. snow$_t$	0.234***	-2.472	-11.86***	0.255***
	(0.0480)	(4.224)	(3.357)	(0.0475)
Snow risk$_t$	-0.147***	-18.74***	-10.43**	-0.127***
	(0.0318)	(2.961)	(4.171)	(0.0360)
Bank Equity^{reg} × Exp. snow$_t$	-0.00122***			-0.000661
	(0.000333)			(0.00103)
Bank Equity^{reg} × Snow risk$_t$	0.000702***			0.00142**
	(0.000251)			(0.000638)
Bank Equity^{grp,reg} × Exp. snow$_t$		0.623***	-0.0177	
		(0.0570)	(0.0619)	
Bank Equity^{grp,reg} × Snow risk$_t$		-0.0137	0.555***	
		(0.0478)	(0.0712)	
N	325096	325096	325096	325096
R^2	0.168			0.167
Firm-Season FE	YES	YES	YES	YES
Week FE	YES	YES	YES	YES
β_1/β_0	-0.00			-0.01
P-Value	0.03			0.05
F-Test of excluded instruments		123.32	73.87	
Angrist-Pieschke F-Test		133.14	64.49	
Endogeneity test (p-value)				0.09

Table 9: Horse race: Bank equity vs. number of banks

This table reports results for regressions explaining the weekly employment days of temporary workers of hotels in Austrian ski resorts during the years 1998-2006. We focus on the starting weeks of the skiing season. The dependent variable is defined in expression (2). We use explanatory variables measuring the expected snow and snow risk in a resort-week, based on data about the last five skiing seasons. See expression (4) for formal definitions. Bank equity is defined as the average equity ratio of all banks located in a 20 kilometer radius around a ski resort, measured at the level of the banking groups to which the banks belong, e.g., the group of savings banks. It is de-meaned and defined in terms of basis points. The number of banks is defined as the number of distinct banking groups in a 20 kilometer radius around a ski resort. In parentheses, we report standard errors clustered at the ski-resort level. *,**,*** indicate statistical significance at the 10%, 5% and 1% levels respectively.

	Log(employment days)		
Exp. snow$_t$	0.235***	0.213***	0.211***
	(0.0497)	(0.0468)	(0.0467)
Snow risk$_t$	-0.126***	-0.121***	-0.118***
	(0.0324)	(0.0312)	(0.0310)
Bank Equity^{grp,all} × Exp. snow$_t$		-0.00127**	-0.00153**
		(0.000636)	(0.000637)
Bank Equity^{grp,all} × Snow risk$_t$		0.000972***	0.00118***
		(0.000346)	(0.000335)
# of Banks × Exp. snow$_t$	-0.0547	-0.0438	-0.0457
	(0.0435)	(0.0428)	(0.0422)
# of Banks × Snow risk$_t$	0.0537*	0.0511*	0.0583**
	(0.0278)	(0.0276)	(0.0270)
Bank Equity^{grp,all} × # of Banks × Exp. snow$_t$			-0.000623
			(0.000619)
Bank Equity^{grp,all} × # of Banks × Snow risk$_t$			0.00113***
			(0.000278)
N	325096	325096	325096
R^2	0.167	0.168	0.168
Firm-Season FE	YES	YES	YES
Week FE	YES	YES	YES

Table 10: Horse race: Bank equity vs. bank branch network diversification

This table reports results for regressions explaining the weekly employment days of temporary workers of hotels in Austrian ski resorts during the years 1998-2006. We focus on the starting weeks of the skiing season. The dependent variable is defined in expression (2). We use explanatory variables measuring the expected snow and snow risk in a resort-week, based on data about the last five skiing seasons. See expression (4) for formal definitions. Bank equity is defined as the average equity ratio of all banks located in a 20 kilometer radius around a ski resort, measured at the level of the banking groups to which the banks belong, e.g., the group of savings banks. It is de-meaned and defined in terms of basis points. Branch diversification measures the degree of geographic expansion of the branch network of the "average bank" in a 20 kilometer radius around a ski resort. For a formal definition, see 4.1. In parentheses, we report standard errors clustered at the ski-resort level. *,**,*** indicate statistical significance at the 10%, 5% and 1% levels respectively.

	Log(employment days)		
Exp. snow$_t$	0.240***	0.220***	0.231***
	(0.0493)	(0.0457)	(0.0480)
Snow risk$_t$	-0.133***	-0.130***	-0.149***
	(0.0319)	(0.0307)	(0.0320)
Bank Equity^{grp,all} × Exp. snow$_t$		-0.00106	-0.00117*
		(0.000686)	(0.000683)
Bank Equity^{grp,all} × Snow risk$_t$		0.000718**	0.000796**
		(0.000348)	(0.000342)
Branch Diversification × Exp. snow$_t$	-0.0853**	-0.0619	-0.0451
	(0.0430)	(0.0461)	(0.0478)
Branch Diversification × Snow risk$_t$	0.0929***	0.0785***	0.0560*
	(0.0269)	(0.0271)	(0.0301)
Bank Equity^{grp,all} × Branch Diversification × Exp. snow$_t$			-0.000726
			(0.000609)
Bank Equity^{grp,all} × Branch Diversification × Snow risk$_t$			0.00113***
			(0.000341)
N	325096	325096	325096
R^2	0.168	0.168	0.168
Firm-Season FE	YES	YES	YES
Week FE	YES	YES	YES

Table 11: Horse race: Bank equity vs. liquidity creation

This table reports results for regressions explaining the weekly employment days of temporary workers of hotels in Austrian ski resorts during the years 1998-2006. We focus on the starting weeks of the skiing season. The dependent variable is defined in expression (2). We use explanatory variables measuring the expected snow and snow risk in a resort-week, based on data about the last five skiing seasons. See expression (4) for formal definitions. Bank equity is defined as the average equity ratio of all banks located in a 20 kilometer radius around a ski resort, measured at the level of the banking groups to which the banks belong, e.g., the group of savings banks. It is de-meaned and defined in terms of basis points. We use the definition of Berger and Bouwman (2009) to define the liquidity creation capacity, LCC, as the weighted sum of liquid and illiquid assets and liabilities. We scale LCC by total assets and calculate the average of all banks in a 20 kilometer radius around a ski resort. In parentheses, we report standard errors clustered at the ski-resort level. *,**,*** indicate statistical significance at the 10%, 5% and 1% levels respectively.

	Log(employment days)		
Exp. snow$_t$	0.299***	0.217***	0.271***
	(0.0524)	(0.0464)	(0.0529)
Snow risk$_t$	-0.152***	-0.168***	-0.211***
	(0.0352)	(0.0336)	(0.0402)
Bank Equity^{grp,all} $\times$ Exp. snow$_t$		-0.00605***	-0.00591***
		(0.000865)	(0.000847)
Bank Equity^{grp,all} $\times$ Snow risk$_t$		0.00128**	0.00110*
		(0.000626)	(0.000624)
LCC/TA^{grp,all} $\times$ Exp. snow$_t$	0.280***	0.566***	0.558***
	(0.0458)	(0.0603)	(0.0593)
LCC/TA^{grp,all} $\times$ Snow risk$_t$	-0.0196	-0.0731	-0.0681
	(0.0349)	(0.0496)	(0.0481)
Bank Equity^{grp,all} $\times$ LCC/TA^{grp,all} $\times$ Exp. snow$_t$			-0.00144**
			(0.000664)
Bank Equity^{grp,all} $\times$ LCC/TA^{grp,all} $\times$ Snow risk$_t$			0.00110***
			(0.000402)
N	325096	325096	325096
R^2	0.172	0.179	0.179
Firm-Season FE	YES	YES	YES
Week FE	YES	YES	YES

Table 12: Risk sharing and labor market tightness. Early season

This table reports results for regressions explaining the weekly employment days of temporary workers of hotels in Austrian ski resorts during the years 1998-2006. We focus on the starting weeks of the skiing season. The dependent variable is defined in expression (2). We use explanatory variables based on information about snow conditions known before the start of a season, and variables describing within-season variation in the snow conditions. The former variables are based on data about the last five skiing seasons and measure the expected snow conditions and snow risk in a ski resort-week. See expression (4) for formal definitions. $Snow_t$ denotes a dummy variable indicating whether there was enough snow for skiing during a resort-week. Bank equity is defined as the average equity ratio of all banks located in a 20 kilometer radius around a ski resort, measured at the level of the banking groups to which the banks belong, e.g., the group of savings banks. It is de-meaned and defined in terms of basis points. We split our sample into two subgroups according to the labor market tightness of the county in which the firm operates. The labor market tightness is defined as $(1 - \text{unemployment rate}_{c(i),T})$ in county $c(i)$ and year T. In parentheses, we report standard errors clustered at the ski-resort level. *,**,*** indicate statistical significance at the 10%, 5% and 1% levels respectively.

	Log(employment days)			
	High LMT		Low LMT	
Within-season				
$\text{Snow}_t - \text{Exp. snow}_t$	-0.0233	-0.0283	0.0642***	0.0653***
	(0.0314)	(0.0312)	(0.0243)	(0.0234)
Ex-ante				
Exp. snow_t	0.178**	0.113	0.297***	0.316***
	(0.0821)	(0.0781)	(0.0607)	(0.0622)
Snow risk_t	-0.134***	-0.137***	-0.0840**	-0.0802**
	(0.0465)	(0.0443)	(0.0389)	(0.0404)
$\text{Bank Equity}^{grp,all} \times \text{Exp. snow}_t$		-0.00221***		0.00131
		(0.000810)		(0.000910)
$\text{Bank Equity}^{grp,all} \times \text{Snow risk}_t$		0.000943*		0.000178
		(0.000513)		(0.000480)
N	154456	154456	166824	166824
R^2	0.202	0.204	0.140	0.140
Firm-Season FE	YES	YES	YES	YES
Week FE	YES	YES	YES	YES

Erklärung gem. §12 Abs. 4 über die genutzten Hilfsmittel

"Hiermit versichere ich, dass ich die vorliegende Arbeit ohne unzulässige Hilfe Dritter und ohne Benutzung anderer als der angegebenen Hilfsmittel angefertigt habe; die aus fremden Quellen direkt oder indirekt übernommenen Gedanken sind als solche kenntlich gemacht. Weitere Personen waren an der geistigen Herstellung der vorliegenden Arbeit nicht beteiligt. Insbesondere habe ich nicht die Hilfe eines Promotionsberaters in Anspruch genommen. Dritte haben von mir weder unmittelbar noch mittelbar geldwerte Leistungen für Arbeiten erhalten, die im Zusammenhang mit dem Inhalt der vorliegenden Dissertation stehen. Ich bezeuge durch meine Unterschrift, dass meine Angaben über die bei der Abfassung meiner Dissertation benutzten Hilfsmittel, über die mir zuteil gewordene Hilfe sowie über frühere Begutachtung meiner Dissertation in jeder Hinsicht der Wahrheit entsprechen."

Berlin, 5. Juli 2020

Simon Baumgartner